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Bond Funds and Credit Risk

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This Draft: March 28, 2022

Abstract

We show that supply-side effects arising from the bond holdings of open-end mutual funds affect corporate credit risk. In our model, funds exposed to flow-performance relationships are reluctant to roll over bonds of companies with weak cash flow prospects fearing future outflows. This lowers rollover prices, enhancing equityholders' strategic default incentives, engendering a positive association between bond funds' presence and credit risk. Empirically, we find that in firms with weak cash flow prospects, fund holding shares increase CDS spreads, and more so when flows are more sensitive to performance. We use instrumental variables and quasi-experiments to address endogeneity concerns.

JEL classification: G23, G32

Keywords: Fund flows, credit risk, flow concerns, bond rollover, default-liquidity loop

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1. Introduction

Since the turn of the century, the U.S. corporate bond market has experienced a large shift in its investor base. As shown in Figure 1, the open-end mutual funds' corporate bond holdings more than doubled from 8.4% to 18.8% between 1998 and 2017, whereas the combined share of pensions and insurance firms fell from 46.8% to 34.8% during the same period.

FIGURE 1 HERE

This shift in investor base implies a fundamental change in capital supply in corporate bond markets, as these open-end funds, unlike other institutional investors, face the risk of investor redemptions. Funds care about investor flows since they are compensated via flat assets under management fees, and thus reductions in future flow affect their payoffs directly; in other words, open-ended bond funds are *flow-motivated*. Investor flows, in turn, respond to fund performance generating so-called *flow-performance relationships*.[1] These two factors, when combined with the strategic incentives of equityholders, can increase the credit risk of corporations. For example, a negative outlook for a company rolling over its debt may make bond funds reluctant to participate in the rollover, because future underperformance (e.g., a default or downgrade) may impose higher penalties on funds: while future underperformance imposes financial losses on all investors, open-end funds are exposed to future outflows as well. Such exposure reduces the willingness of funds to participate and fosters credit risk because a failure to negotiate favorable rollover prices increases the firm's cost of capital and tempts equityholders to default. In other words, the incentives of the *suppliers* of capital for corporate bonds may affect the nature of credit risk in the economy.

The literature has not yet examined how the changes in the composition of capital supply, as represented by the emergence of open-end funds, affects rollover risk, focusing instead either on demand-side (i.e., borrower-level) factors or on the role of aggregate market conditions. The former strand of the literature emphasizes how—in the presence of credit market imperfections—firms may face difficulty rolling over short

[1] Papers documenting flow-performance relationships, include Chevalier and Ellison (1997), Sirri and Tufano (1998), Spiegel and Zhang (2013), and Goldstein, Jiang, and Ng (2017) among many others.

term debt when faced with declining collateral values and increasing risk (e.g., Diamond, 1991; Titman, 1992; Gopalan, Song, and Yerramilli, 2014; and Chen, Xu, and Yang, 2021). The latter strand emphasizes how changes in market conditions can exacerbate rollover risk and thus affect credit risk (e.g., Acharya, Gale, and Yorulmazer, 2011; He and Xiong, 2012; He and Milbradt, 2014; Valenzuela, 2016; Chen, Cui, He, and Milbradt, 2017; Choi, Hackbarth, and Zechner, 2018; and Nagler, 2020). In this paper, we propose a novel *supply-side* (i.e., lender-level) channel through which rollover risk may interact with credit risk. We show theoretically that the incentive schemes of capital suppliers may exacerbate rollover risk and demonstrate empirically that the extent to which a firm's bonds are held by open-end funds is causally associated with an increase in its credit risk.

We begin by illustrating the link between the presence of flow-motivated investors at rollover and the strategic default choice of the firm's equityholders using a simple model. We consider a firm with some pre-existing debt that must be rolled over today. Any loss that accrues from rollover can be borne by the firm's equityholders, who have deep pockets.[2] However, if the equilibrium rollover price is too low, equityholders will refuse to bear the losses and strategically default today on the existing debt. Prior to participating in the rollover, all potential investors receive an informative signal about the firm's future cash flows, but the precision of their information differs, and they are unsure about its quality. There are two classes of potential investors: funds and individuals. What distinguishes funds from individuals is that, in addition to profit or losses from buying the bond—which is the only thing that motivates individuals—funds also derive utility from being perceived to be well-informed by their principals. This is a short hand for flow motivations: since funds' clients prefer to invest with well-informed funds, being viewed as being well-informed is likely to enhance future fund inflows. Funds thus contemplate whether their action, i.e., whether to buy the bond at rollover, would enhance or damage their posterior probability of their being viewed as being well informed.

We separately derive the equilibrium bond prices with flow-motivated funds and profit-motivated individuals and compare the two. The equilibrium bond price with funds carries a component that reflects their flow motivations; when investing in the bond hurts (improves) expected posterior reputation and thus expected

[2] Thus, in our model, as in He and Xiong (2012), there are no costs associated with the issuance of equity, and default arises purely endogenously.

future flows, the funds' equilibrium willingness to pay falls (rises). This leads the bond prices to differ depending on whether the investors at rollover are funds or individuals: in particular, rollover prices are more sensitive to future firm prospects in the presence of flow-motivated funds.

Our model generates two main empirical implications. First, a greater presence of bond funds at rollover implies that the current default risk will be higher for firms whose future cash flow prospects are relatively weak. Funds are reluctant to invest in such firms because of the anticipated negative impact of future underperformance on future fund flows. Such reluctance is relevant in reality because, as we discuss in Section 3.1, the average bond mutual fund holds a relatively concentrated portfolio, so that each investment matters for future fund performance. Funds' reluctance to invest reduces the bond price that can be achieved at rollover and tempts equityholders to default today, leading to a positive association between bond funds' presence at rollover and credit risk. A key implication of our model is that flow motivations have an *asymmetric* effect. That is, while flow motivations could also lead funds to overbid at rollover when the firm has strong cash flow prospects, under such circumstances, equityholders will not default anyway, so the presence of funds will not impact credit risk. Thus, the effect of flow-motivated bondholders will be asymmetric, clustered amongst firms with relatively weak cash flow prospects at rollover. Second, when bond funds are more strongly flow motivated, their increased reluctance to invest translates into deeper underpricing at rollover for firms with weak cash flow prospects, strengthening the effect on firm credit risk.

We empirically explore the link between bond funds and credit risk using data on the bond holdings of mutual funds and the credit default spread (CDS) spreads of bond issuers for the period between 2001 and 2015. For each firm-month, we compute the share of its outstanding bonds held by active bond mutual funds, which we refer to fund holding share (FHS) of corporate bonds. We then examine whether FHS has a material impact on a firm's credit risk as reflected in CDS spreads. However, given that FHS and a firm's credit risk are likely to be determined simultaneously, our analysis is susceptible to potential endogeneity problems. For example, mutual funds are known to invest in firms with higher credit spreads to "reach for yield."[3] To address

[3] Reaching for yield has been documented for various types of investors, e.g., for insurance firms (Becker and Ivashina, 2015), money market funds (DiMaggio and Kacperczyk, 2017), and bond mutual funds (Choi and Kronlund, 2018).

this issue, we use the instrumental variable (IV) approach of Koijen and Yogo (2019) throughout our empirical analysis, which is motivated by the idea that an investment mandate of a mutual fund is pre-determined and should be exogenous to contemporaneous shocks to firms' credit risk. Our IV exploits exogenous variation in mutual funds' demand for corporate bonds, which is driven by the cross-sectional composition of mutual funds that include these bonds in their mandates.

Our two-stage least squares regression using the IV *à la* Koijen and Yogo (2019) indicates that a one-standard-deviation increase in FHS increases a firm's credit risk by around 22 to 28 bps, almost a fifth of the average CDS spread of our sample firms. Moreover, consistent with our first theoretical prediction, we document a strong asymmetry in the relationship: the positive relationship between FHS and CDS spread is only in evidence among firms rated BBB or below, i.e., firms with weak cash flow prospects. In contrast, we do not find a significant relationship between FHS and CDS spread among firms rated A or above. Similarly, interacting FHS with the firm's one-year stock return reveals that the increased presence of bond funds has a more pronounced impact on a firm's credit risk only for those with poor stock performance.

To further correct for potential endogeneity between fund holdings and credit risk, we follow Adelino, Cheong, Choi, and Oh (2021) by focusing on plausibly exogenous changes to FHS arising from Morningstar's star rating methodology for fund share classes that turn five years old. Morningstar's overall star rating uses three-, five-, and ten-year star ratings, each of which is constructed using a fund's risk-adjusted return ranking over the specified horizon relative to its category peers. The overall star ratings of funds aged between 36 and 59 months consist exclusively of the three-year rating. When the fund turns five, however, Morningstar begins to use both three- and five-year star ratings with 40% and 60% weights, respectively, to calculate the overall star rating. This means that, a fund's performance between three and five years ago—i.e., purely "stale information"—can raise or lower the overall star rating at the five-year mark. Yet, we find that flows respond to this largely mechanical change, leading to a significant increase in FHS among firms held by upgraded five-year-old funds compared with those held by funds that are not upgraded at the five-year mark. Exploiting this exogeneous FHS change in a difference-in-difference setting, we show that the credit risk of the firms increases *pari passu* with their FHS, lending further support to a causal link between fund holding share and credit risk.

We perform two additional tests of our model implications, which further help alleviate any endogeneity concerns. We focus first on the rollover channel. Our model conceptualizes that the presence of bond funds *at rollover* elevates a firm's level of credit risk. If so, the effect of FHS on credit spreads should be *stronger* when rollovers are imminent. Our results support this hypothesis. A one-standard-deviation increase in FHS increases the five-year CDS premium by around 22 bps in the absence of a maturing bond, but the corresponding figure rises to 56 bps during the month when a firm faces a bond maturity, confirming the relevance of the rollover channel in driving up credit risk. Next, we also examine the differential effects of fund holdings on credit risk by focusing on times of market distress. We find that the positive effect of FHS on CDS spreads is much stronger when the default spread or VIX is high. These results, combined with those obtained from the rollover analysis, further help us distinguish our channel from the potential reverse causality channel working through the risk-taking of mutual funds, e.g., reaching for yield. As is shown in previous studies, risk-taking incentives such as reaching for yield tend to be weaker, not stronger, during high-risk periods, which stands in sharp contrast to our results from these conditional analyses.

We then test the second prediction of the model that the positive relationship between FHS and CDS premium strengthens for funds with greater flow concerns. Our proxies for funds' exposure to outflow risk include past fund performance, fund flow volatility, management company size, and rear load fees. We find that the holding share of funds with poor recent return or high flow volatility has a more significant positive impact on CDS spreads. Likewise, the holding share of funds belonging to large families with better intra-family liquidity provisions or those with a high share of load fee classes—which inhibits investor flow response—has a weaker impact on the CDS premium.

We utilize another quasi-experimental setting—the departure of Bill Gross from Pacific Investment Management Company (PIMCO) in September 2014—to isolate the impact of funds' flow concerns in difference-in-differences regressions. The sudden departure of the "Bond King" from PIMCO, the largest management company in the U.S. bond fund market, was unthinkable at the time and unsettled PIMCO's investors. As many investors chose PIMCO funds solely because of the track record of Bill Gross, his unexpected departure substantially raised uncertainty in fund flows, which can thus be deemed a plausibly exogenous increase in PIMCO fund managers' flow concerns. We therefore compare firms held by PIMCO against all other sample firms or those held by Prudential or Vanguard, the next two largest management companies for U.S. bond funds, in a [-6, 6] month window around Bill Gross' departure. For firms with over 5% of PIMCO holding share prior to Bill Gross' departure, we find that their credit risk increases by 11 to 14 bps relative to control firms following his departure. Further analysis shows that the increase in credit spread is driven by the increased concerns regarding flow volatility rather than the immediate impact of PIMCO's fire sales to meet redemption demands. These findings highlight the economic relevance of funds' flow concerns in exacerbating the positive relationship between fund holdings and credit risk.

Our analysis is complementary to the literature on the concavity of the flow-performance relationship faced by bond mutual funds (Goldstein, Jiang, and Ng, 2017), which arises due to a first-mover advantage for withdrawing investors (Chen, Goldstein, Jiang, 2010) in funds that invest in illiquid assets. While the results in these studies turn on how investors in bond mutual funds react to each other's anticipated outflows, we study how the anticipation of such outflows affects the behavior of fund managers, and how this—in turn—affects corporate managers' incentives to default. Our qualitative effects do not rely on any concavity in the flow-performance relationship, but if funds are exposed to disproportionately greater downside risk via their flow performance relationship, our quantitative results will be strengthened. We illustrate this connection in two ways. First, we use a simple extension of the baseline model to show that the relationship between the presence of flow-motivated bondholders and credit risk becomes more pronounced as the flow-performance relationship itself becomes more concave. Second, we empirically examine how the concavity of the flow-performance relationship affects the relationship between FHS and CDS premium. We find that the positive association between FHS and CDS premium is stronger in funds with more pronounced degrees of flow-performance concavity, but a relationship remains even among low-concavity funds. Thus, our results are quantitatively strengthened by concavity but not driven by it.

Related literature. Our paper contributes to the literature on rollover risk discussed above. As already noted, in contrast to the prior focus within this literature on demand-side or market-level factors, we highlight a novel *supply-side* factor, namely the flow motivations of mutual funds. We argue that the identity of who holds a firm's bonds may matter for its credit risk. More broadly, we extend the vast literature on credit risk, beginning with Merton (1974) and the literature on credit default swaps (see Augustin, Subrahmanyam, Tang, and Wang (2014) for a survey). Second, our study also contributes to the vast literature on the financial stability and fund flows associated with the open-end structure of mutual funds. Earlier studies document fund flows exert ex-post price effects through flow-induced trading by mutual funds (e.g., Coval and Stafford, 2007). A growing body of studies also show that the open-end structure of mutual funds can exacerbate fund run risk and financial fragility (e.g., Chernenko and Sunderam, 2016; DiMaggio and Kacperzcyk, 2017; Zeng, 2017; Choi, Hoseinzade, Shin, and Tehranian, 2020; Chernenko and Sunderam, 2020; Jin, Kacperczyk, Kahraman, and Suntheim, 2022) and also exert financial and real effects on their stock holdings (Edmans, Goldstein, and Jiang, 2012; Khan, Kogan, and Serafeim, 2012;) and bond holdings (Chernenko and Sunderam, 2012; Ben-Rephael, Choi, and Goldstein, 2021; Zhu, 2021). Our contribution to the literature lies in showing that these flows, through their effect on the fund manager's incentives, not only affect fund liquidity and run risk but also the credit risk of firms they hold by depressing their bond rollover prices.

Finally, our study is related to the literature on the asset pricing and corporate governance implications of the flow motivations of asset managers. On the asset pricing side, for equities, Dasgupta, Prat, and Verardo (2011) find that trading behavior consistent with flow motivations is associated with cross sectional return predictability, while for bonds, Cai, Han, Li, and Li (2019) document that herding behavior consistent with flow concerns generates price impact. On the governance side, a growing literature (see Dasgupta, Fos, and Sautner, 2021 for a survey) documents how the flow concerns of equity blockholders can impact firm value. In contrast, we are the first to study the effect of the flow concerns of corporate *creditors* and show how such incentives translate into real impact via their effect on corporate credit risk.

2. Model

2.1. Main Set-Up

To illustrate the effect of flow-motivated bond funds on corporate credit risk, we start with a simplified, two-date version of continuous-time models of strategic default by equityholders (e.g., Leland and Toft, 1996; He and Xiong, 2012), and extend it to introduce flow-motivated institutional bondholders, i.e., bond funds.

Consider a firm that generates terminal cash flow $V \in \{0,\ \bar{V}\}$ at $t = 2$, where $\bar{V} > 1$. The firm is owned by equityholders with deep pockets but subject to limited liability. Since we are interested in debt rollover, we assume that the firm has pre-existing debt in the form of a discount bond with face value 1 maturing at $t = 1$. There is no cash flow at $t = 1$, and so the firm's maturing bond must be rolled over at $t = 1$ with a new discount bond with face value 1 maturing at $t = 2$. Investors must decide at $t = 1$ whether to purchase this new bond, i.e., whether to refinance the firm, and how much to pay for it. We denote by p the equilibrium price of the new bond.[4]

To repay the pre-existing bondholders, the shortfall $1 - p$ is made up by the firm's existing equityholders; since equityholders have deep pockets—as in He and Xiong (2012)— there is no constraint to the issuance of new equity at $t = 1$ if the equityholders choose to bail out the bondholders. If, however, the equityholders decline to provide new equity, the firm defaults and all future cash flows are seized by the pre-existing bondholders. The discount rate is zero for simplicity, and all agents are risk neutral.

Let us denote the public prior of V at $t = 1$ with $\gamma_V = \Pr(V = \bar{V})$, which reflects the firm's future cash flow prospects. We use γ_V and cash flow prospects interchangeably throughout this section. Then:

Proposition 1 (Interim strategic default). Strategic default occurs at $t = 1$ whenever $p \leq 1 - \gamma_V(\bar{V} - 1)$.

[4] We assume for simplicity throughout that each investor is small relative to the size of the bond issue, and thus neglects the effect of his own rollover decision on the possibility of strategic default by equityholders.

Proof. If the equityholders default at $t = 1$, their payoff is 0 because of their limited liability. However, if the equityholders decide to bail out the pre-existing bondholders, their expected payoff is given by:

$$\underbrace{\gamma_V(\bar{V} - 1)}_{\text{High firm cash flow at } t=2} + \underbrace{(1 - \gamma_V) \cdot 0}_{\text{Low firm cash flow at } t=2} - \underbrace{(1 - p)}_{\text{Rollover losses at } t=1} \quad (1)$$

Thus, equityholders will default strategically whenever (1) is less than or equal to 0, i.e., whenever $p \leq 1 - \gamma_V(\bar{V} - 1)$ as in the proposition. □

We now endogenize the rollover equilibrium price p. Throughout our analysis, to minimize the number of frictions in the model, we assume that investors at rollover are competitive. This implies that, in the rollover game, investors will bid up to their full willingness to pay. Since our interest is in excessively *low* rollover prices, any rent extraction by investors as a result of imperfect competition would simply exacerbate the phenomena.

For expositional ease, we present our rollover analysis in two separate parts. First, in section 2.2, we assume that (all) investors are flow-motivated bond funds. Then, in section 2.3, we shut down flow motivations, so that (all) investors may be interpreted as individuals or more patient institutions. Given this separation, we can also simplify the analysis by abstracting from rollover *quantities*. In other words, we assume that the required rollover quantity is small enough that the firm can successfully roll over by charging the willingness to pay of the most optimistic investor present. In the real world, both flow-motivated and patient investors will be present simultaneously, and the required rollover quantity may affect the identity of the *marginal* investor. Our qualitative findings hold in such settings, as discussed in section 2.6.

2.2. Flow-Motivated Investors

Suppose first that the population of investors consists of bond funds, i.e., delegated agents, evaluated at $t = 2$ by their principals. Funds conduct research on the firm's terminal cash flow and decide whether to buy the bond issued at $t = 1$. Suppose that each fund can be one of two types, good or bad, denoted $\tau \in$

$\{G, B\}$, with the ex ante probability that the fund is of the good type denoted $\gamma_\tau = \Pr(\tau = G)$. The two types differ in the precision of their information; each fund receives a signal at $t = 1$, denoted s, which satisfies

$$\Pr(s = V^* | V = V^*, \tau = \tau^*) = \sigma_{\tau^*} \text{ for each } V^* \in \{0,\ \bar{V}\} \text{ and } \tau^* \in \{G, B\}. \tag{2}$$

To simplify the analysis, suppose that $\sigma_G = 1$ and $\sigma_B = 1/2$. In other words, good types observe the firm's terminal cash flow with certainty, while the signal of a bad type is no better than noise. However, in the tradition of signal jamming models beginning with Holmstrom and Ricart-i-Costa (1986), we assume that funds do not know their own types. While this assumption—common in the signal jamming literature—simplifies the analysis, it is worth noting that Dasgupta and Prat (2008) show that incentives in this class of models are qualitatively similar even if agents have information about their types, as long as such self-knowledge is not perfect. Each fund's action is denoted a, with $a = 1$ if the fund chooses to buy the bond or $a = 0$ if not. We further assume that τ and V are independent of each other. We now state the fund's payoff at $t = 2$, given by:

$$\{\min(1, V) - p\} \cdot I(a = 1) + \kappa \Pr(\tau = G | a, V). \tag{3}$$

The first term of (3) represents the fund's profits from bond investment if the manager decides to buy the bond. The second term represents the fund's additional gains from taking actions likely to be viewed by the principal as being indicative of good type. In other words, the principal evaluates the fund on the basis of her action and the eventual cash flow, and if the action and the cash flows are such that the principal's posterior probability of a fund being of the good type, i.e., the fund's "reputation," improves, the manager is rewarded in the form of additional flows, for example. This flow additionally compensates the fund, and κ then measures the fund's intensity of flow motivation. Microfoundations for such payoff functions can be found in Dasgupta and Prat (2008) and Guerrieri and Kondor (2012).

In reputational cheap-talk models, it is usually possible for both pooling and separating behavior to arise in equilibrium. In the former type of equilibrium, funds choose actions that are not contingent on their private signals, while in the latter their actions are informative about their signals. It is only in separating equilibria that funds are rewarded (or penalized) for making correct (or incorrect) choices on the equilibrium path, since choices are correlated with information, and information is correlated with underlying ability. Given the evidence on positive flow-performance relationships faced by bond funds (e.g., Goldstein, Jiang, and Ng, 2017), we focus on separating equilibria.[5] Then, upon assuming the payoff function as in (3), we derive the following proposition regarding the equilibrium price:

Proposition 2 (Equilibrium with flow-motivated bondholders). There exists an equilibrium where:

(i) The fund chooses $a = 1$ if $s = \bar{V}$,

(ii) The fund chooses $a = 0$ if $s = 0$,

(iii) The firm sets the price of the new bond at:

$$p = \Pr(V = \bar{V}|s = \bar{V}) + \kappa\{E(\Pr(\tau = G|a = 1, V)|s = \bar{V}) - E(\Pr(\tau = G|a = 0, V)|s = \bar{V})\}. \quad (4)$$

Proof. See the Internet Appendix, Section A. □

In this equilibrium, only funds with high signal ($s = \bar{V}$) participate in the rollover game and buy the bond, while those with the low signal decide not to participate. Knowing that only the high signal funds participate, the firm sets the price equal to their full willingness to pay, which contains two components. The first term in (4) is the high signal funds' expectation of the bond's terminal cash flow at $t = 2$. However, in addition to this fundamental value, the second term represents the fund managers' additional willingness to pay arising from their flow motivations. Upon receiving a favorable signal, funds evaluate how their purchase decision is likely to affect their principals' posterior assessment of their type being good or bad when the terminal cash flow is realized. If buying the bond (i.e., $a = 1$) increases the funds' likelihood of being viewed as the good type at $t = 2$ compared to staying out of the rollover game, they have an additional reason to participate in the rollover; the reverse holds if funds are less likely to be viewed as being of the good type. The second term in (4) captures the expected reputation gain or loss – i.e., flow rewards or penalties – to high signal funds from participating in the rollover vs. not doing so. Thus, the price in (4) extracts the high-signal funds'

[5] For the interested reader, we argue in the internet appendix (see Section B) that, under reasonable off-equilibrium beliefs, the key effect of bond funds' flow motivations on corporate credit risk remains qualitatively unchanged even in pooling equilibria.

full willingness to pay. At the equilibrium price, therefore, high-signal funds are indifferent between rollover or not. Given that high-signal funds are indifferent between rollover or not at equilibrium prices, the less optimistic low-signal funds will clearly strictly prefer not to participate, thus completing the equilibrium argument.

In the above equilibrium, posterior reputation—and thus, implicitly, flow—is positively correlated with correct choices; funds can only improve their $t = 2$ reputation relative to the $t = 1$ prior by buying at $t = 1$ bonds that subsequently do *not* default at $t = 2$ or by declining at $t = 1$ to buy bonds of companies that do default at $t = 2$.

2.3. Investors without flow motivations

We now consider investors without flow motivations, which corresponds to the case of $\kappa = 0$. These investors are "standard" profit-maximizing agents, whom we casually refer to as individuals to distinguish them from flow-motivated funds in the previous subsection. However, in practice, these investors need not be individuals; any institutional investor with less pronounced short-term flow considerations may behave in a similar manner. The following proposition, which we state without proof, then follows immediately:

Proposition 3 (Equilibrium with standard profit-maximizers). There exists an equilibrium where:

(i) The individual chooses $a = 1$ if $s = \bar{V}$,

(ii) The individual chooses $a = 0$ if $s = 0$,

(iii) The firm sets the price of the new bond at $p = \Pr(V = \bar{V} | s = \bar{V})$.

2.4. Comparison of equilibria with flow-motivated vs. standard investors

We now compare the equilibrium bond prices derived in the previous two subsections. For ease of exposition, we refer to the equilibrium bond price with flow-motivated investors in Proposition 2 as p_f^*, and the price with standard investors in Proposition 3 as p^*. We show that:

Proposition 4 (Comparing equilibrium bond prices). $p_f^* \leq p^*$ if and only if $\gamma_V \leq \frac{1}{2}(1 - \gamma_\tau)$.

Proof. See the Internet Appendix, Section A. □

In other words, flow-motivated funds act as punitive buyers at rollover in firms with relatively low prospects of generating successful cash flow. This is because, as γ_V gets progressively smaller, despite having observed $s = \bar{V}$, high signal funds believe it to be progressively less likely that V will turn out to be $\bar{V}$, and thus—since in equilibrium it is only desirable to be seen to have invested when $V = \bar{V}$—their flow-driven willingness to pay diminishes, progressively reducing p_f^* relative to p^*. The opposite is true as γ_V gets progressively large. Our analysis is illustrated in Figure 2, which plots the rollover prices of flow-motivated and profit maximizing bondholders (the solid black and dashed gray curves, respectively) and the strategic default threshold (the light straight line). Cash flow prospects, γ_V, are depicted on the x-axis. The solid black curve crosses the dashed gray curve from below at $\frac{1}{2}(1-\gamma_\tau)$, illustrating Proposition 4.

FIGURE 2 HERE

2.5. Asymmetric impact of flow motivations on credit risk

We now complete the baseline analysis by identifying conditions under which there is a class of firms with low cash flow prospects for which strategic default occurs if and only if investors are flow motivated. We also show that, under the same condition, even though flow motivated investors underpay for low cash-flow prospect firms and overpay for high cash-flow prospect firms, such differences in willingness to pay affects default risk *only* for low cash flow prospect firms.

Clearly, underpricing fostered by the presence of flow motivated investors can be irrelevant for credit risk if equityholders' strategic default occurs quite frequently, i.e., for all values of γ_V that satisfy $p_f^* < p^*$. This can be avoided by assuming (realistically) that strategic default is ex ante infrequent, i.e., that $\bar{V}$ is not too small, giving equityholders sufficient upside at $t = 2$. For such $\bar{V}$, the highest value of γ_V for which strategic default can occur is strictly smaller than $\frac{1}{2}(1-\gamma_\tau)$. To see this in Figure 2, note that a high value of $\bar{V}$ ensures that the strategic default threshold is steep enough to intersect the (dashed gray) p^* and (solid black) p_f^* curves to the left of $\frac{1}{2}(1-\gamma_\tau)$. Strategic default arises for a given type of investor if and only if γ_V is to the left of the intersection of the light straight line with the pricing curve corresponding to that type of investor. Whenever the light straight line intersects the pricing curves to the left of $\frac{1}{2}(1-\gamma_\tau)$, the intersection with the dashed gray line is strictly north-west of the intersection with the solid black line. Then, there is a range of γ_V for which strategic default occurs if and only if investors are flow motivated. Further, since the intersections are to the left of $\frac{1}{2}(1-\gamma_\tau)$, for strong cash flow prospect firms, with $\gamma_V > \frac{1}{2}(1-\gamma_\tau)$, strategic default never arises with or without flow motivated investors; hence the willingness of flow motivated investors to overpay for such firm's debt at rollover has no impact on credit risk. Formally:

Proposition 5 (Flow motivations and credit risk). There exists a $\hat{V} > 1$ such that for $\bar{V} > \hat{V}$:

i. There is a positive measure set of γ_V contained in $\left(0, \frac{1}{2}(1-\gamma_\tau)\right)$ for which strategic default arises if and only if investors are flow motivated.

ii. For $\gamma_V > \frac{1}{2}(1-\gamma_\tau)$, flow motivated investors have no impact on strategic default.

Proof. See the Internet Appendix, Section A. □

Thus, the presence of flow-motivated bondholders has an *asymmetric* effect: it affects the default probability only for firms with *low* cash-flow prospects at rollover.

2.6. Flow-motivated and non-flow motivated investors simultaneously present

In Sections 2.2 through 2.5, we qualitatively illustrated our core mechanism by separately considering flow-motivated and non-flow-motivated investors, which also enabled us to ignore the role of rollover quantity. In reality, both types of investors are simultaneously present. We now discuss how our analysis extends to such settings.

Imagine that the firm requires to roll over K bonds each with face value 1. There is sufficient non-flow-motivated capital to absorb $K_{NF} \geq 0$ of such bonds, while there is sufficient flow-motivated capital to absorb $K_F \geq 0$ of such bonds, where $K_{NF} + K_F > K$. Thus, the analysis of Section 2.2 can be thought of as a special case in which $K_{NF} = 0$, while the analysis of section 2.3 can be viewed a special case in which $K_{NF} > K$. Assuming finite amounts of available non-flow-motivated and flow-motivated capital implicitly requires some friction (e.g., limits to arbitrage or market segmentation), as underpricing or overpricing cannot arise in a frictionless setting. In Section 3.1 we discuss in detail why such frictions may exist in the primary market for corporate bonds.

Firms with weak cash flow prospects, i.e., those with $\gamma_V \leq \frac{1}{2}(1-\gamma_\tau)$, can charge p^* per refinanced bond to non-flow-motivated refinancers but only $p_f^* < p^*$to flow motivated bond funds. Thus, they will sell as much as possible to non-flow motivated investors. Hence, if $K_{NF} > K$, then such firms will sell only to non-flow-motivated investors, rendering non-flow-motivated investors marginal buyers. On the other hand, if $K_{NF} < K$, then these firms will first raise $K_{NF}p^*$ from non-flow-motivated investors and will sell the remainder to bond funds raising $(K - K_{NF})p_f^*$. Thus, the total capital that can be raised by the firm is $K_{NF}p^* + (K - K_{NF})p_f^*$, which is clearly decreasing in $K - K_{NF}$ since $p_f^* < p^*$.[6] In other words, the subsidy that equity holders must provide to prevent default *increases* in $K - K_{NF}$, i.e., in the measure of flow-motivated funds to whom they must sell at rollover, increasing their incentives to default strategically.

2.7. Concave flow-performance relationships

In our model, learning about funds' ability endogenously generates reputational rewards and punishments, which proxy for an increasing flow-performance relationship. For simplicity, we have specified a single parameter κ in (3) to capture the impact of such reputational rewards and punishments on the fund. Such a simple characterization draws on prior microfoundations in the career concerns literature (e.g., Dasgupta and

[6] This discussion assumes that it is possible to engage in differential pricing at rollover. However, the qualitative effects would be similar under uniform pricing. Then, the total capital that can be raised by the firm would be a step function in K_{NF} instead of the linear function shown above but would remain increasing in K_{NF}, as above.

Prat, 2008). At an applied level, this specification is tantamount to assuming a *linear* flow-performance relationship, whereby reputational rewards are treated symmetrically to reputational punishments. Despite the assumed *symmetry* of reputational rewards and punishments, our analysis shows that the impact on corporate behavior is endogenously asymmetric, as discussed in Section 2.5. Clearly, if, for some extraneous reason, funds were to experience *asymmetrically* high disutility from reputational losses relative to utility from reputational gains, our endogenously asymmetric effect would be strengthened.

In this context, it is relevant that the empirical literature shows that the flow-performance relationship of bond funds to be concave (Goldstein, Jiang, and Ng, 2017), suggesting that reputational losses matter more to funds than gains of the same magnitude. The theoretical underpinnings of this effect can be traced to strategic complementarity amongst investors in illiquid bond funds: withdrawals by some investors may incentive withdrawal by others, leading to a feedback loop and excess withdrawals (Chen, Goldstein, and Jiang, 2010). While a full model combining fund-level flow concerns and investor-level complementarity is beyond the scope of this paper, we can illustrate the additional effect of concavity by a two-parameter specification, where reputational gains are captured by a parameter κ_G while losses are captured by a separate parameter κ_L with $\kappa_L > \kappa_G$. This would mean that, in the region where incremental reputational rewards from rollover are negative, i.e., the flow-premium is negative, the equilibrium rollover price with flow motivated funds would decline more steeply in cash-flow prospects than in the baseline case, leading to a *higher* incidence of strategic default. Formally, this is equivalent to the analysis of Section 2.2 with a contingent κ as follows:[7]

$$\kappa = \begin{cases} \kappa_G & \text{if } \gamma_V > \frac{1}{2}(1-\gamma_\tau), \\ \kappa_L & \text{if } \gamma_V \leq \frac{1}{2}(1-\gamma_\tau). \end{cases}$$

3. Testable Implications, Data, and Variables

3.1. Testable implications

[7] The statement and proof of Proposition 2 would follow as in Section 2.2, replacing κ by its contingent equivalent.

The main testable implications of our model may be summarized as follows.

(i) The presence of mutual funds at the time of rollover increases credit risk for firms with weak cash flow prospects.

(ii) Funds with stronger flow concerns will be more reluctant to participate in debt rollovers for firms with weak cash flow prospects, strengthening the effect of fund presence on credit risk.

(iii) Funds with a more concave flow-performance relationship will exacerbate the effect of fund presence on credit risk.

In our empirical analysis, we take these model predictions to the data. Before doing so, we provide a discussion of the empirical relevance of some key aspects of our model.

First, the model has only one firm. The discerning reader may wonder if, in reality, bond funds have diversified portfolios so that a default in one firm does not matter quantitatively to them. In our data, however, on average bond funds hold relatively concentrated portfolios of 66 firms, which contrasts with 173 firms for equity funds (see Table 1). Such a high concentration in portfolio holdings implies that, with a 40% percent recovery rate, a default in a single firm can result in a portfolio loss of over 0.9% and even higher losses if defaults are correlated across firms.

Second, our model implicitly assumes some frictions in the primary market, because, in a frictionless market, there will always be sufficient mass of non-flow-motivated investors who would provide rollover capital to firms at fair prices, eliminating underpricing. Such frictions in the primary market can arise from a persistent investor base in the corporate bond market, which makes it difficult for firms to change their capital providers or for investors to participate in new bond issuance in the primary market. This persistence in the investor base can arise because the issuer-underwriter-investor relationships are sticky and costly to switch, facilitating recurring participation in rollover by existing bondholders. It can also arise due to lower information acquisition costs for existing bondholders who may already have conducted necessary research and monitoring of their investments, particularly when firms' credit risk is high and information asymmetry is severe. Using our data, we document that issuer-underwriter-investor relationships are highly persistent. Table A.1 in the Internet

Appendix reveals that 86.7% of corporate bond issuances are underwritten by a lead underwriter who has underwritten at least one previous issuance by the same issuer within the past three years. In a similar vein, 96.3% of funds' primary market purchase involves a lead underwriter that they have previous experience with within the past three years.[8]

Such persistence also helps us to find a proxy for the presence of active funds at the time of bond rollover, which is not directly observable. In particular, given the persistence in issuer-underwriter-investor relationships, we use the holding share of a firm's outstanding bonds by active mutual funds, which we refer to as fund holding share (FHS), as our main explanatory variable.

3.2 Data

We use five main sources of data: (i) Morningstar Direct for the holdings of U.S. taxable bond funds, (ii) the Center for Research in Security Prices (CRSP) Mutual Funds database for information on fund characteristics, (iii) the Mergent Fixed Income Security Database (FISD), (iv) the Trade Reporting and Compliance Engine (TRACE) for bond trades, and (v) the Markit credit default swap (CDS) database for CDS pricing data.

3.2.1. Mutual fund data

Using the fund holdings data from Morningstar from 2001 through 2015, we first match fund share-class level identifier used by Morningstar (*secid*) with that of the CRSP Mutual Funds database (*crsp_fundno*) using CUSIP in a similar manner to Pástor, Stambaugh, and Taylor (2015). We consider bond funds that are classified as corporate or general according to the CRSP objective code as in Goldstein, Jiang, and Ng (2017) and Choi and Kronlund (2018);[9] a total of 1,128 funds satisfy the criteria. Over a half of holdings information of these

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[8] Related results can be found in Zhu (2021). DiMaggio, Kermani, and Song (2017), Hendershott, Li, Livdan, and Schürhoff (2020), Nikolova, Wang, and Wu (2020), and Nagler and Ottonello (2021) all show that underwriter/dealer and investor relationships tend to be persistent because of underwriter favoritism, trading network relationships, or costly acquisition of information on issuers. Daetz, Dick-Nielsen, and Nielsen (2018) and Chakraborty and MacKinlay (2019) also show that issuer-underwriter relationships tend to be highly persistent.

[9] Specifically, these are funds with CRSP objective codes I, ICQH, ICQM, ICQY, ICDI, ICDS, or IC, which corresponds to Lipper objective codes A, BBB, IID, SII, SID, USO, HY, GB, FLX, MSI, or SFI.

bond funds in Morningstar are in monthly frequency, with the rest mostly in quarterly or semi-annual frequencies, with the latter only in a few isolated instances. Following Elton, Gruber, and Blake (2011a; 2011b), we use the latest available holdings information within the past six months. We obtain further information on each fund using the CRSP Mutual Funds databases.

3.2.2 CDS premium data

We measure the credit risk of bond issuers using CDS spreads. Unlike corporate bond spreads, CDS spreads are standardized (e.g., constant maturities) and less subject to market microstructure issues including illiquidity pricing premium and therefore are a cleaner measure of credit risk than bond spreads, which allows us a fair cross-sectional comparison of firms' credit risk. The Markit CDS data provide daily CDS spreads for maturities ranging from 6 months to 30 years. We use monthly five-year CDS spreads on senior unsecured obligations denominated in U.S. dollars as they are the most widely traded contracts.[10]

3.3. Main variable construction

We construct our main explanatory variable, FHS, defined as the fraction of total bond amounts of an issuer held by active bond funds, using our holdings data. At each month-end, we first sum bond amounts held by our sample funds for each corporate bond of a firm.[11] We then aggregate each bond-month observation into firm-month observation and calculate fund holding share by dividing the amount of aggregated active fund bond holdings by the total amount of bonds outstanding for the firm. We also consider an alternative version of FHS by dividing active fund holdings with the total amounts debt (including other forms of debt such as bank loans) and obtain consistent results.[12]

Using fund returns and total net assets from the CRSP Mutual Funds databases, we calculate the flow of fund i at month t. Share class level data are aggregated at the fund level using the CRSP identifier *crsp_cl_*

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[10] We focus on contracts with modified restructuring documentation clause until April 2009 and those with no restructuring clause thereafter in light of the "CDS Big Bang."
[11] Bonds with Morningstar *sectype* code B, BF, or BI are classified as corporate bonds.
[12] See Table A.8 in the Internet Appendix for more detail.

grp with TNAs at the previous month-end as the weight. For a detailed definition of each variable in our study, refer to Appendix C in the Internet Appendix.

3.4. Instrumental Variable

Identifying a causal relationship between FHS and CDS spreads suffers from a potential simultaneity problem. Although our model predicts that the presence of flow-motivated funds at rollover should positively affect credit risk among weak cash flow prospect firms, we cannot rule out the possibility that unobservable factors drive both funds' demand for bonds and the credit risk of bond issuers. One such example would be the risk-taking behavior of investors, also commonly referred to as "reaching for yield." For example, Becker and Ivashina (2015) find that insurance firms tilt their corporate bond portfolio toward firms with higher credit spreads within the same rating to take advantage of regulatory arbitrage. Choi and Kronlund (2018) show reaching for yield in mutual funds when interest rates and volatilities are low. In such cases, a simple OLS specification is insufficient in delineating our model's predictions from these alternative stories.

To alleviate this endogeneity concern, we employ an IV approach in our main regression analyses. In particular, we instrument FHS using hypothetical fund holding share based on the investment universe of mutual funds, following the approach of Koijen and Yogo (2019). For each fund at each month-end, we construct a hypothetical portfolio that equally divides the fund's total net assets over its investment universe, which is measured as a set of all issuers whose bonds have been held by the fund at least once within the last three years. This measurement of the investment universe is also based on Koijen and Yogo (2019) who argue that institutional investors typically limit portfolio holdings to a relatively small set of investments and that the set of investments that they have held rarely changes over time. We refer to the equal-weighted holdings based on a fund's investment universe as its hypothetical holdings. To construct the IV for FHS for firm k at month t, we aggregate the hypothetical holdings of all funds and divide them by the total amounts of bonds outstanding for firm k. We use this IV for FHS in two-stage least square (2SLS) regressions.

The idea behind this instrument is that bond mutual funds have stable and predetermined investment universes reflecting investment mandates specified in their prospectuses, often with industry, size, maturity, and credit rating constraints on what assets they hold. In addition, high costs of acquiring firm-specific information further restricts a fund's potential investment universe. Thus, our IV exploits variation in bond funds' demand that arises mainly from their investment universes; that is, when a bond is included in the investment universe of many funds, the bond is likely to have a high fund holding share than other bonds. Since the investment universe of bond mutual funds is largely predetermined and the hypothetical holdings allocate a fund's total net assets equally, regardless of individual firms' credit risk, we may reasonably expect this investment-universe-based demand for a firm's bonds to be largely exogenous. This in turn allows us to exploit plausibly exogenous variations in funds' demand for corporate bonds to alleviate the simultaneity and reverse causality issues. It is worth noting that, in its reliance on fund-level capital allocation, this instrument is quite close to the spirit of the model, in which there are exogenous supply effects from investors that determine the marginal prices of these bonds. In most empirical analyses that follow, we thus present the second-stage results of two-stage least squares (2SLS) panel regressions.

3.5. Summary statistics

Table 1 presents the summary statistics of our sample of 570 firms between Oct. 2001 and Oct. 2015, with firm-level fund holdings data constructed using 1,128 corporate and general fixed income funds. The average five-year CDS spread for our sample is around 130 bps. While the average CDS spread of high investment-grade (AAA to A) firms stands at around 60 bps, those of BBB and high yield firms are in excess of 110 bps and 330 bps, respectively. Our variable of interest, FHS, has the mean and median of 30.2% and 26.0%, respectively. We observe substantial cross-sectional variation in FHS, with the standard deviation exceeding 21% and the inter-quartile range of over 27%. We further report that, in line with the trend of sustained investor inflows into bond funds throughout our sample period,[13] average fund holding share in our sample increases over time (untabulated); FHS, for example, increases from 21.7% in 2002 to 32.0% by 2013.

TABLE 1 HERE

[13] Between 2009 and 2018, more than $2.2 trillion has moved into bond mutual funds, according to ICI Factbook (2019).

4. Empirical Results

We first test our main empirical predictions that FHS increases the credit risk of fund holdings for weak cash prospect firms (sections 4.1, 4.2, and 4.3) and that this effect of FHS on credit risk is stronger when funds' flow sensitivity is higher (sections 4.4 and 4.5). Then we examine the implications of concavity in flow performance relationships (section 4.6).

We employ three distinct approaches to address potential endogeneity concerns. First, our regression results are based on the IV approach as described in the previous section. Second, we exploit a mechanical upgrade in the Morningstar star rating that is based on stale information, which provides an exogenous increase in FHS for upgraded funds. Third, we exploit a quasi-experiment setting in which funds' flow concerns are exogenously heightened, following the departure of Bill Gross from PIMCO.

4.1. Fund holdings and credit risk

Our first testable prediction states that the presence of flow-motivated funds would have little impact on credit risks of firms with good cash flow prospects, but it should have a significantly positive impact on the credit risk of those with weak cash flow prospects. Thus, on average, the overall relationship between FHS and CDS premium should be positive in the full sample. To test this prediction, we first run the following 2SLS regression:

$$FHS_{i,t} = \beta_0 + \beta_1 \cdot Counterfactual\ FHS_{i,t} + \beta \cdot Controls_{i,t} + \varepsilon_{i,t}, \text{ (first stage)} \quad (5)$$

$$CDS\ Premium_{i,t+1} = \gamma_0 + \gamma_1 \cdot \widehat{FHS}_{i,t} + \gamma \cdot Controls_{i,t} + \eta_{i,t+1}, \quad \text{(second stage)} \quad (6)$$

where $CDS\ Premium_{i,t}$ is the five-year CDS spread of firm i in month t. The control variables are based on the previous studies on credit risk, for example, Collin-Dufresne, Goldstein, and Martin (2001) and Zhang, Zhou, and Zhu (2009). As firm-level variables, we include the first four moments of stock returns (1-year stock return, volatility, skewness, and kurtosis), log assets, leverage, return on equity, dividend payout per share, and recovery rate. As market-level variables, we include one-month S&P 500 index return, 3-month T-Bill rate, term spread, and VIX. In an alternative specification, we exclude these market variables but include the time fixed effect. We use standard errors robust to heteroskedasticity and two-way clustered by firm and time. Table 2 presents our results.

TABLE 2 HERE

In line with our model's predictions, we find a significantly positive association between FHS and the next-period CDS premium; in both columns, the coefficient on FHS is statistically significant at the 1% level. Moreover, first-stage Kleibergen-Paap F-statistics of over 90 in both instances strongly indicate that our instrument is highly relevant in explaining the actual FHS. In terms of economic magnitude, a one-standard-deviation increase in FHS of 21.36% is estimated to raise the next-month CDS premium by between 22 and 28 bps. Given that the unconditional average CDS premium of our sample is around 135 bps, the estimated increase corresponds to around 15 to 20% of average CDS spread, a sizeable figure.

We proceed to examine whether the positive relationship between FHS and CDS premium is indeed concentrated among firms with weak cash flow prospects. To test this prediction, we consider two proxies of firms' cash flow prospects. First, we interact fund holding share with two mutually exclusive indicator variables, one for those rated A and above and another for those rated BBB or below.[14] Second, we interact FHS with rolling 1-year stock returns of bond issuers. We then run two separate 2SLS regressions after interacting FHS with either credit rating dummies or 1-year stock returns. Table 3 presents our results.

TABLE 3 HERE

As predicted by our model, Panel A reveals that the relationship between FHS and the next-period CDS spread is statistically significant *only* among firms with credit rating below BBB. For firms with A rating or above, we do not find a similarly statistically significant relationship between FHS and the CDS spread, and the point estimates on FHS, if anything, are negative. The differences in these two interaction coefficients exhibit high statistical significance with F-statistics exceeding 20 in both instances. In terms of economic magnitude, a one-standard-deviation increase in FHS among firms rated BBB or below (22.92%) is associated

[14] We split our credit rating subsample at the A-BBB boundary because high yield firms constitute a relatively small percentage of our sample, as shown in Table 1.

with a 23-bp to 30-bp increase in the next-period CDS premium. Given that the average CDS spread of the firms rated BBB or below stands at 174 bps, the increase amounts to around 15% of the average spread.

In Panel B, we report panel regression results with the addition of the interaction term between FHS and 1-year stock return, which similarly turns out to be significantly negative at the 10% level in column (1) and 1% level in column (2). The estimated coefficients in column (2) with time fixed effect imply that, for a firm with its 1-year stock return at the third quartile of our sample, i.e., 30.2%, a one-standard-deviation increase in FHS increases the next-period CDS premium by around 17 bps. In contrast, for a firm with its latest 1-year stock return at the first quartile of -6.2%, the corresponding figure is almost 30 bps.[15] Taken together, Table 3 highlights that the effect of active mutual funds' holding share on the reference firm's credit risk is particularly prominent among those with weak cash flow prospects as our model suggests.

Moreover, the strong association between bond holdings and CDS premia among weak cash flow prospect firms appears largely limited to active bond funds, which are subject to flow concerns. When we examine the holding shares of insurance companies, pension funds, or passive funds, i.e., major types of investors in the corporate bond market who are less subject to performance-based flow concerns—in Table A.3 in the Internet Appendix—we find no positive association with credit risk.

4.2. The introduction of five-year Morningstar star rating and credit risk

While our IV approach is designed to tease out causal relationships between fund holdings and credit risk, it is desirable to also examine exogenous shocks to fund holdings. To this end, following Adelino, Cheong, Choi, and Oh (2021), we focus on the mechanism by which Morningstar assigns an overall star rating to funds when they turn five years old, which arguably creates an exogenous shock to such funds' flows. Morningstar constructs its overall star rating for each share class using three-, five-, and ten-year star ratings. For each time horizon, the star rating is calculated by ranking the share class's Morningstar risk-adjusted return (MRAR) among its category peers over the specified period, with the top 10% rated 5 stars, the next 22.5% 4 stars, and

[15] In Table A.2, we consider shorter return horizons of one and six months, respectively, and re-estimate Table 3 Panel B. Results are qualitatively unchanged.

so on. For share classes aged between 36 months and 59 months, five- or ten-year rating cannot be constructed, so the overall rating consists entirely of the three-year star rating. When a share class turns five, however, a new five-year star rating is introduced. To calculate the overall rating, Morningstar now takes a weighted average of the three- and five-year star ratings with weights of 40% and 60%, respectively, rounding to the nearest integer to determine the overall rating. This means that, even though the three-year star rating remains unchanged when the fund turns five, the share class could still be upgraded or downgraded on the basis of the new five-year star rating. Importantly, any difference in risk-adjusted performance that leads to an upgrade or downgrade stems from how a share class performed between three and five years from the time of rating publication and is thus stale news, unlikely to be correlated with the fundamentals of current holdings. Yet, if investors focus on the overall star rating, as is found to be the case in Ben-David, Li, Rossi, and Song (2021), Evans and Sun (2021) and Reuter and Zitzewitz (2021), investor flows may nevertheless respond.

We first check whether flows respond to a rating change at the five-year mark, despite the mechanical nature of such changes as discussed above. We identify all share classes that reach the age of five whose overall star ratings are either upgraded or remain at their previous levels. The former group forms our treated group, while the latter is our control. Then, we examine flow responses to rating changes using difference-in-difference regressions over [-6, 6] months around the five-year mark. Column (1) of Table 4 shows that upgraded funds receive, on average, extra flows close to 0.5% per month, i.e., nearly 3% over the six-month window following the rating change relative to those that remain at their previous ratings, with the difference-in-difference term significant at the 5% level.

TABLE 4 HERE

We then examine whether an upgrade at the five-year mark leads to a material change in FHS as well as credit risk. Specifically, we first identify all funds with one of its share classes satisfying our treated or control criteria and focus on firms for which treated or control funds have a minimum collective holding weight of 2.5% or 5%. Our next step is to examine, in a difference-in-difference setting, whether firms with more than 2.5% or 5% of their shares held by treated funds experience an increase in FHS and credit risk relative to those that are held mainly by control funds. Columns (2) and (4) of Table 4 show that the FHS of firms that are held by treated funds increase by around 1.5% to 2.1% following rating changes at the five-year mark, with statistical significance at the 1% level, likely emanating from extra inflow of capital. Crucially, columns (3) and (5) further show that this increase in FHS is accompanied by a corresponding increase in CDS premium of around 14 to 22 bps, with the *t*-statistics exceeding 3 in both the columns. The identification exercise in Table 4 thus confirms the main finding of our IV approach, namely a causal link between fund holding share and credit risk.

4.3. Is the rollover channel relevant?

According to the predictions of our model, a positive relationship between FHS and CDS spreads exists because the presence of flow-motivated funds lowers bond prices at rollover. If so, it is reasonable to believe that the more imminent bond rollover is, the more evident should be our effect. Thus, the presence of mutual funds will affect the credit risk of bond issuers especially when the issuers are facing rollover risk.

To explore whether this is the case empirically, we construct the maturity indicator variable, which takes the value of 1 whenever the firm has a bond maturing within the next month. We then re-estimate Table 2 with the interaction of FHS with this indicator variable. This analysis is further intended to alleviate concerns over reverse causality in addition to our instrumental variable approach; to generate a significantly positive coefficient for the interaction term under this alternative story based on "reaching for yield," funds should have a heightened incentive to hold riskier firms right before rollover events, which seems less plausible given that a rollover failure of riskier, illiquid bonds could be particularly costly to these funds.[16] Table 5 presents our results.

TABLE 5 HERE

Table 5 reveals that the effect of FHS on CDS premium more than doubles during the month of a bond maturity. Our estimates in column (2) reveals that a one-standard-deviation increase in FHS increases the CDS spread by around 22 bps in normal times, but the corresponding figure rises to 56 bps during the month preceding a firm's bond maturity. In both instances, the interaction term between FHS and the maturity indicator is significantly positive at the 5% level. In addition to our analysis of the CDS premium, we examine

[16] Jankowitsch, Nagler, and Subrahmanyam (2014), for example, find that riskier and more illiquid bonds recover substantially less after a default event, with poor post-default liquidity in the secondary market (He and Milbradt, 2014).

offering yields (i.e., yields at issuance) in Table A.4 in the Internet Appendix; we find that a larger presence of bond funds is associated with lower rollover yields among weak cash flow prospect firms, which is in line with our prediction and thus provides further support to the relevance of our channel. Put differently, the presence of flow-motivated active funds *just before* a rollover event is perceived by the market as a potential contributing factor to a firm's credit risk.

As an additional analysis on the relevance of our rollover channel, we examine the effect of overall market conditions. Existing studies on reaching for yield find that funds' risk-taking incentives are moderated during market distress times (Choi and Kronlund, 2018), because potential costs of risk-taking also increase in such periods owing to the high illiquidity and high credit risk of the corporate bond market. Thus, we examine whether the relationship between FHS and CDS spread, particularly around bond maturities, is affected by market conditions; this enables us to explore whether the observed patterns are in line with the existing studies on the reaching for yield behavior. To this end, we form two equal-sized subsamples based on each of the following market proxies. First, we form subsamples using whether a given month's default spread, specifically the difference between Baa and Aaa corporate bond yields, is above or below the sample median. Second, we form subsamples in the identical manner using VIX. We then re-estimate our main regressions for each subsample. We further test the subsample differences in coefficients for FHS. Table 6 presents our results.

TABLE 6 HERE

In Panel A, we find that the coefficient on FHS is significantly positive at the 5% level in both subsamples. Furthermore, although the subsample coefficient differences are not statistically significant, the point estimates on FHS have larger magnitudes in high default spread and/or VIX periods. A more interesting result emerges in Panel B, where we consider the interaction of FHS with the maturity indicator variable. We find that the interaction term is significantly positive at the 5% level during periods of high default spread, but insignificant during low default spread periods; the subsample coefficient difference is also marginally significant at the 10% level. That is, the presence of flow-motivated active funds just before a firm's bond maturity has a more pronounced impact on its credit risk during periods of market stress as indicated by the high default spread. The observed patterns are markedly different from those found in the previous studies on reaching for yield, with the effect of FHS on credit risk substantially *stronger* during periods of market stress.

4.4. Credit risk and fund flow concerns

We now turn our attention to the second testable implication: the positive relationship between flow-motivated funds' holdings and credit risk should be more pronounced when the funds exhibit higher degrees of flow concerns. Specifically, one corollary of Proposition 2 in our model is that, whenever the flow-motivated funds find it in their interest to under-bid for the bond, the extent of under-bidding will be more severe as their flow concerns intensify. We thus examine the circumstances under which fund managers' flow concerns are more pronounced. First, given the evidence of concave flow-performance relationship documented for bond funds (Goldstein, Jiang, and Ng, 2017), we expect flow concerns, especially those related to outflows, to be more severe for poorly performing, i.e., lower-ranked, funds. Second, flow concerns are likely to be greater among funds whose investor flows tend to be more volatile. Third, flow concerns will likely be more pronounced for funds belonging to a small family, because larger families have various means at their disposal to provide liquidity to those experiencing temporary outflows (Bhattacharya, Lee, and Pool, 2013; Agarwal and Zhao, 2019). Finally, the presence of a high load fee should dampen investor response and alleviate the fund's flow concerns.

To analyze whether there exist differential effects of FHS on credit risk for funds with these different characteristics, we proceed as follows. At each month-end, we split our sample of funds into high versus low groups based on the sample median of following variables within each Lipper category: (i) latest 12-month fund return, (ii) latest 12-month fund flow volatility, (iii) management firm size, and (iv) the asset share of load fee classes within the fund. In Table 7, we then re-estimate column (2) of Table 2 using the high- and low-group fund holding shares instead.[17] Table 7 presents our results.

TABLE 7 HERE

[17] In each case, we separately construct the high- and low-group counterfactual holding shares to instrument for these two variables.

Column (1) of Table 7 indicates that the holding shares of funds with relatively low 12-month return has a larger positive impact on the CDS premium, as shown by the coefficient estimate on the low-return group's FHS (1.257), which is statistically significant at the 1% level. Column (2) shows that the holding share of high flow-volatility funds has a substantially stronger impact on the CDS premium, with the coefficient difference between the high and low groups' holding shares significant at the 5% level. Similarly, columns (3) and (4) also indicate that the holding share of funds belonging to smaller families and funds with low load fee classes have a significantly more pronounced impact on the next-period CDS premium. All these findings are in line with our model's prediction that the degree of flow motivations (i.e., κ) exacerbates the relationship between FHS and credit risk.

4.5. Changes in the intensity of flow motivations: the departure of Bill Gross from PIMCO

To test the prediction that the degree of flow motivation exacerbates the relationship between FHS and credit risk, it is ideal to identify a setting where flow motivations change as a result of exogenous shocks. To this end, we use the sudden departure of Bill Gross from PIMCO in September 2014. Bill Gross was one of the co-founders of PIMCO and managed its famous Total Return Fund. Dubbed the "Bond King" by popular media, he was one of the most influential investors in the bond market, with Morningstar stating in 2010 that "[no] other fund manager made more money for people than Bill Gross."[18] However, he surprisingly left PIMCO in September 2014 for Janus Capital and sued his former employer soon afterward, citing fierce in-fighting among PIMCO executives.

The sudden departure of Gross shocked investors. PIMCO without Bill Gross was almost unthinkable at the time. Many investors had chosen PIMCO based on the long track record of Gross. Uncertainty about the likely performance of the new management team increased flow concerns for PIMCO funds: Even a hint of underperformance may induce investors to leave PIMCO. Indeed, as we show in Table A.5 in the Appendix, PIMCO funds' flow-performance sensitivity increased substantially after Gross's departure.

[18] From "Announcing the Morningstar Fund Managers of the Decade (Jan. 12, 2010)" (available at: https://www.morningstar.com/articles/321713/announcing-the-morningstar-fund-managers-of-the-de)

Importantly, the increase in flow concerns following Bill Gross's departure was not directly related to the fundamentals of PIMCO holdings. We therefore use the departure of Bill Gross in a difference-in-difference setting to uncover the effect of increased flow concerns on credit risk. Specifically, using the latest available portfolio holding in August 2014, i.e., just before Bill Gross' departure, we identify treated firms as all firms (i) held by PIMCO or (ii) those with PIMCO holding share greater than 5%. As control firms, we either use all other sample firms or those held by Prudential and Vanguard (Zhu, 2021).[19] Then, for the window of [-6, 6] months around the departure of Bill Gross, we run the following regressions:[20]

$$CDS\ Premium_{i,t+1} = \gamma_0 + \gamma_1 \cdot PIMCO\ dummy_{i,t} \times Post\ Bill\ Gross_{i,t} + \gamma \cdot Controls_{i,t} + \eta_{i,t+1}, \tag{7}$$

where the PIMCO indicator variable takes the value of one when a firm's corporate bond is held in nonzero quantities (or with holding share of over 5%) by PIMCO in August 2014, and the post-Bill Gross departure indicator takes the value of one for all sample observations after the departure of Bill Gross. We use the identical set of control variables as before, with firm and time fixed effects.[21] According to the predictions of our model, the interaction term between the PIMCO indicator and post-Bill Gross departure indicator should have a positive sign.

TABLE 8 HERE

Table 8 Panel A presents the results for all firms held by PIMCO prior to the departure of Bill Gross. We find that the difference in CDS spread between these PIMCO-held firms and other sample firms increases by 4 bps after the departure of Bill Gross, with the corresponding figure rising to 7 bps when we restrict the control firms to be Prudential- or Vanguard-held firms. In both instances, this difference-in-difference term is statistically significant at the 1% level. When we interact this term with credit rating indicators in columns (3) and (4), we find the increase in CDS spread difference to be concentrated almost entirely around firms rated BBB or below. These results are consistent with the predictions of our model, whereby the heightened intensity

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[19] Whenever we consider firms with PIMCO holding share greater than 5%, we also compare these firms to those with Prudential and/or Vanguard holding share greater than 5%.

[20] We do not include the standalone PIMCO dummy or post-Bill Gross departure dummy because they are perfectly collinear with firm and time fixed effects, respectively.

[21] Our results are robust to a longer difference-in-difference window, as shown in Table A.6 in the Internet Appendix.

of flow concerns strengthens the positive relationship between fund holdings and credit risk primarily among weak cash flow prospect firms. When we consider firms with PIMCO holding share exceeding 5% in Panel B, we find even stronger results in terms of economic magnitude. We find that the CDS spread difference between our treated and control firms increases by 11 to 14 bps following the departure of Bill Gross. Once again, the effect is primarily concentrated around firms rated BBB or below.

FIGURE 3 HERE

Figure 3 plots the CDS spread of treated firms vs. the CDS spread of our two sets of control firms around Bill Gross's departure. In both Panels A and B, there is no noticeable trend in the difference between the CDS spreads of PIMCO-held versus control firms prior to Bill Gross's departure. However, the plot reveals a sizeable increase in this difference after his departure, which remains significant and noticeable until the end of our test window in March 2015.

FIGURE 4 HERE

The fact that the gap in CDS spreads persists throughout the second half of our test window suggests that this pattern is driven by heightened flow *concerns* rather than the *realized* outflows from PIMCO. To see this, note that Figure 4 Panel A shows that the wave of investor outflows from PIMCO largely disappeared by around January 2015, but the CDS spread gap between PIMCO-held vs. control firms remains persistent through the end of March 2015. Further, Figure 4 Panel C shows that there is no significant decrease in overall FHS among PIMCO-held firms relative to Prudential- or Vanguard-held firms around the time of Bill Gross' departure, with other funds filling the void created by PIMCO's asset sales,[22] suggesting that potential fire sales of bonds held by PIMCO funds cannot account for the observed patterns in the CDS spread.

FIGURE 5 HERE

Figure 5 shows further evidence that our treated firms witnessed a sharp increase in weighted average flow volatility of their active bondholders.[23] This increase could be attributed to either PIMCO's own flow volatility increase and/or (on average) higher flow volatility of funds that increased their bond position in firms

[22] We confirm this to be the case for Janus Capital, Prudential, and Vanguard in Figure A.1 in the Appendix.
[23] As discussed earlier, Table A.5 in the Internet Appendix confirms a similar pattern in a difference-in-difference regression setting.

sold by PIMCO. Overall, our difference-in-difference analysis thus shows how active fund bondholders' heightened flow concerns translates into higher credit risk of firms.

4.6. Credit risk and concave flow-performance relationship

The final prediction of our theory states that the relationship between fund holdings and credit risk should be more pronounced when mutual fund bondholders face a concave flow-performance relationship, because the fear of a large outflow following poor recent performance heightens the manager's downside flow concerns, further depressing her willingness to invest in bonds. This concave flow-performance relationship is known to stem from the payoff complementarity that arises from open-end funds' liquidity mismatch (Chen, Goldstein, and Jiang 2010). As a result, flows become disproportionately more sensitive to bad performance. We examine how flow-performance concavity affects the effect of FHS on credit risk as follows. First, we estimate flow-performance concavity using a rolling three-year regression of monthly fund flow on the interaction of lagged fund return and negative fund return indicator. The coefficient on the interaction term then captures extra flow response to a negative return relative to a positive return of the same magnitude. We use this coefficient to group our sample funds into high- and low-concavity funds based on the sample median of their Lipper peers at each month-end. Then, as in Table 7, we separately calculate the holding share of each group and re-estimate our main results. Table 9 presents our results.

TABLE 9 HERE

Column (1) of Table 9 Panel A reports the baseline regression results with high- and low-concavity FHS. We find that the positive relationship between FHS and the next-period CDS spread is more pronounced among high-concavity funds, though the coefficient difference test between the two groups yields an insignificant result. Credit rating interaction results in column (2) also suggest that, once again, the strong association between FHS and credit risk among firms rated BBB or below is more pronounced for high-concavity funds. However, even among low-concavity funds, we find a significant relationship between FHS and credit risk for firms rated BBB or below, indicating that our results are not driven by concavity alone.

Finally, we check the relation between FHS and firms' cash flow volatility. With a concave flow-performance relationship, we expect bond funds to shun firms with high volatility, which will affect FHS. As reported in Table A.7 in the Internet Appendix, we do not find a strong association between FHS and cash flow volatility measures, showing that flow-performance concavity is not likely a main driver for FHS.

5. Conclusion

We show that firms with a large share of their corporate bonds held by bond mutual funds subsequently experience an increase in credit risk. Our model illustrates how the flow concerns of bond funds reduce their willingness to pay for bonds of firms with weak cash flow prospects, which in turn intensifies the equityholders' strategic default incentives and worsens the firm's credit risk. The positive relationship between bond funds and credit risk strengthens as funds' flow concerns intensify and if the flow-performance relationship becomes more concave. Overall, our conceptual framework suggests that, in addition to firm fundamentals and market characteristics, *who* holds the bonds is a relevant factor in determining a firm's credit risk.

Our empirical analyses support the model's predictions. After controlling for potential endogeneity issues by using an instrumental variable that exploits the funds' cross-sectional variations in total net assets and their investment universe, we find that a one-standard-deviation increase in the holding share of active bond funds increases a firm's next-period CDS premium by over 20 bps, particularly for firms rated BBB or below. We further confirm the causal relationship using a mechanical change in Morningstar's rating methodology for funds turning five years old, with a quasi-exogenous inflow into upgraded five-year-old funds resulting in increased fund holdings and subsequent credit risk. The economic relevance of fund holding share on credit risk increases substantially ahead of a firm's debt maturity, confirming the importance of the rollover channel at work in the model, and our results are stronger in turbulent market periods, further distinguishing our findings from "reaching for yield" by bond funds. This relationship becomes stronger in statistical and economic significance when the funds holding the firm's bonds are susceptible to flow fragility because of poor returns, high flow volatility, low TNA share of load fee classes, or small size of their fund families. We further address endogeneity concerns inherent in the relationship between fund holdings and credit risk by using Bill

Gross' departure from PIMCO in 2014 as an exogenous shock to PIMCO funds' flow concerns, showing that heightened flow concerns can have a material impact on the credit risk of firms that these funds hold. Finally, we show that the relationship between fund holdings and credit risk becomes stronger when funds holding the bonds exhibit high degrees of flow-performance concavity.

Our theoretical and empirical results are highly relevant in the context of the changing landscape of the market for corporate bonds. The bond holdings of bond funds in the corporate bond market have more than doubled in the previous two decades, and they are the only group of U.S. domestic institutional investors with a growing presence in the market, filling the gap created by the declining share of more traditional investors. Our results indicate that this could be a cause for concern from the issuers' perspective. The fragility of these funds' flow base and the resulting flow concerns of fund managers could prove an obstacle to a firm's bond rollover and exacerbate its credit risk, particularly during times of credit stress and market uncertainty. If so, our results further suggest that better monitoring of a firm's existing bond investor base should form an integral part of future regulatory approaches to ensure financial stability of the market for corporate debt financing.

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Table 1. Summary Statistics

In this table, we report summary statistics on the sample of 570 firms with five-year CDS spread data available on Markit and non-missing coverage of at least one of its corporate bonds in the Morningstar fund holdings data. Our sample period is between October 2001 and October 2015, with the holdings data of 1,128 corporate and general fixed income funds. The observations are at the firm-month level. All firm-level continuous variables are winsorized at the 1% and 99% levels, and we report the summary statistics computed using winsorized values. We further provide fund portfolio characteristics at the fund-quarter level, with bond fund holdings from Morningstar and equity fund holdings from Thomson Reuters s12. For a detailed description of how each variable is constructed, refer to Appendix C in the Internet Appendix.

	Obs.	Mean	St. Dev.	P25	P50	P75
CDS premium						
All firms	45,667	134.72	191.45	39.37	71.84	146.25
AAA to A	15,809	60.98	71.50	25.09	43.33	69.84
BBB	21,592	113.49	125.37	46.53	80.68	134.10
BB or below	8,266	331.19	318.59	119.60	234.51	417.87
Fund holding share (FHS)						
All funds (%)	45,667	38.21	22.27	22.06	36.17	52.54
Active funds only (%)	45,667	30.18	21.36	14.26	26.02	41.74
Passive funds only (%)	45,667	7.759	8.235	0.000	5.967	12.83
Other characteristics						
1-month stock return (%)	45,666	1.021	8.647	-3.526	1.060	5.426
6-month stock return (%)	45,667	6.514	23.45	-5.815	6.431	18.43
12-month stock return (%)	45,667	13.29	34.92	-6.239	12.14	30.23
Historical volatility (annualized %)	45,667	32.23	18.35	20.48	27.18	37.40
Historical skewness	45,667	0.0898	0.857	-0.243	0.0739	0.404
Historical kurtosis	45,667	4.518	6.930	1.110	2.207	4.688
Total assets ($ millions)	45,667	47,623.1	118,500.4	6,064	14,302	32,279
Leverage (%)	45,667	46.74	22.52	30.79	43.29	58.68
Return on equity (%)	45,667	5.416	12.99	2.638	5.185	8.113
Dividend payout per share ($\times 100$)	45,667	0.511	0.508	0.131	0.421	0.733
S&P 500 index return (%)	45,667	1.877	21.61	-11.27	-2.869	10.65
3-month T-Bill rate (%)	45,667	1.444	1.741	0.070	0.900	2.230
Term spread (%)	45,667	2.030	1.144	1.550	2.210	2.920
VIX	45,667	20.09	8.696	13.88	17.40	23.70
Fund portfolio characteristics						
No. of public firms held in the portfolio						
Bond mutual funds	91,466	66.07	59.07	25	53	89
Equity mutual funds	111,174	173.1	331.0	52	82	143

Table 2. Fund Holdings and Credit Risk

We report the second-stage results of two-stage least squares firm-month level panel regression of CDS premium (in bps) on fund holding share (FHS). To construct an instrumental variable for a firm, we aggregate the hypothetical holdings of funds and divide them by the total amounts of bonds outstanding for the firm. The hypothetical holdings are calculated as the equal-weighted holdings that equally divide a fund's total net assets over its investment universe. In column (1), we include market-wide control variables without fixed effects, while in column (2), we include time fixed effects. Control variables are 1-year return, realized volatility, skewness, and kurtosis, recovery rate, firm size, leverage, ROE, and dividend payout per share, and in the case of column (1), 1-month S&P 500 return, 3-month T-Bill rate, term spread, and VIX. All controls are lagged by one month. We further report the Kleibergen-Paap F-statistic for the weak instrument test. *t*-statistics based on standard errors that are robust to heteroskedasticity and two-way clustered by firm and time are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: 5-year CDS spread (bps)	
	(1)	(2)
FHS (%)	1.310***	1.008***
	(3.51)	(2.81)
1-year stock return (%)	-0.904***	-1.188***
	(-7.45)	(-11.02)
Historical volatility (%)	5.112***	7.048***
	(9.51)	(13.74)
Historical skewness	1.197	5.400**
	(0.52)	(2.42)
Historical kurtosis	0.071	-0.965***
	(0.21)	(-3.07)
Recovery rate	-15.999***	-15.610***
	(-5.55)	(-5.32)
Log assets	-12.148***	-12.295***
	(-4.78)	(-4.81)
Leverage (%)	1.843***	1.705***
	(7.45)	(7.69)
ROE (%)	-0.837***	-0.607***
	(-3.26)	(-3.10)
Dividend payout per share	-19.841***	-3.557
($\times 100$)	(-2.75)	(-0.57)
1-month S&P 500 return (%)	0.605***	
	(3.70)	
3-month T-Bill rate (%)	-13.145***	
	(-3.99)	
Term spread (%)	-16.073***	
	(-3.00)	
VIX	-0.932	
	(-1.26)	
Time FE	NO	YES
Kleibergen-Paap F-statistic	100.88	96.30
No. of obs.	45,462	45,459

Table 3. Fund Holdings, Cash Flow Prospects, and Credit Risk

In this table, we estimate the two-stage least squares regressions of CDS spreads as in Table 2, albeit with fund holding share (FHS) either interacted with two mutually exclusive credit rating dummies (A or above vs. BBB or below) or past 1-year stock return. In Panel A, we interact FHS with two indicator variables, namely an indicator variable for credit ratings of A or above and another with credit ratings of BBB or below. In Panel B, we interact FHS with past 1-year stock returns. In the untabulated first stage regression, our instrumental variable, i.e., hypothetical FHS, is also interacted with credit rating indicator variables or 1-year stock returns in the identical manner. We also report F-statistics from the hypothesis testing that the coefficient estimates on the two interaction terms are equal. In column (1), we include market-level control variables without fixed effects, while in column (2), we include time fixed effects. Control variables are identical to those in Table 2, whose coefficient estimates are omitted for brevity. *t*-statistics based on standard errors that are robust to heteroskedasticity and two-way clustered by firm and time are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Credit rating interactions

	Dependent variable: 5-year CDS spread (bps)	
	(1)	(2)
FHS ×	-0.193	-0.239
I(A or above) (%)$^{(A)}$	(-0.42)	(-0.53)
FHS ×	1.310***	1.004***
I(BBB or below) (%)$^{(BBB)}$	(3.53)	(2.80)
F-statistic: (A) = (BBB)	32.68***	20.60***
Controls	YES	YES
Time FE	NO	YES
No. of obs.	45,462	45,459

Panel B. Interaction with 1-year stock return

	Dependent variable: 5-year CDS spread (bps)	
	(1)	(2)
FHS (%)	1.500***	1.276***
	(3.44)	(3.09)
FHS ×	-1.218*	-1.662***
1-year stock return (%)	(-1.83)	(-2.67)
1-year stock return (%)	-0.448*	-0.553**
	(-1.82)	(-2.28)
Controls	YES	YES
Time FE	NO	YES
No. of obs.	45,462	45,459

Table 4. Difference-in-Difference Test: Morningstar Rating Change at the Five-Year Mark

In this table we estimate the effect of Morningstar star rating changes on fund holding share (FHS) and CDS spreads when a fund reaches the age of 5 years. We first identify all events when a share class of a fund reaches the five-year old mark and its star rating either goes up (our treated share classes) or remains the same (the control share classes). In column (1), we run the share class-level difference-in-difference regression of fund flows for a window of [-6, 6] months around these events. The indicator variable, *Upgrade at 5-year*, takes the value of one for the treated and zero otherwise. The indicator variable, *Post 5-year*, takes the value of one for the window of [0, 6] months after the event. In columns (2) and (3), we run the firm-level difference-in-difference regressions of next-month FHS and CDS spreads around the same event windows and using firms with treated or control fund holding share greater than 2.5%. The firm-level indicator variable, *Upgrade at 5-year*, takes the value of one if the firm is held by treated funds in the month prior to the event. The indicator variable, *Post 5-year*, is defined as in column (1). In columns (4) and (5), we run the same regressions as in columns (2) and (3) but we only use firms with treated or control fund holding share greater than 5%. The control variables are the same as those in Table 2. *t*-statistics based on standard errors that are robust to heteroskedasticity and clustered by time are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable				
	Monthly flow (%)	FHS (%)	CDS spread	FHS (%)	CDS spread
	(1)	(2)	(3)	(4)	(5)
	5-year classes	Holding share > 2.5%		Holding share > 5%	
Upgrade at 5-year	-0.528***	-0.974*	-5.624*	-1.903***	-7.007*
	(-2.71)	(-1.97)	(-1.68)	(-2.68)	(-1.72)
Post 5-year	-0.245**	0.278	-9.667***	0.059	-19.043***
	(-2.04)	(0.73)	(-2.83)	(0.12)	(-4.34)
Upgrade at 5-year ×	0.479**	1.473***	13.729***	2.087***	22.427***
Post 5-year	(2.20)	(2.72)	(3.27)	(2.89)	(4.57)
Controls	NO	YES	YES	YES	YES
Firm FE	NO	YES	YES	YES	YES
Time FE	NO	YES	YES	YES	YES
Adjusted R-squared	0.000	0.493	0.798	0.520	0.817
No. of obs.	48,637	18,523	18,523	12,409	12,409

Table 5. Fund Holdings and Credit Risk around Bond Maturities

In this table we present the estimation results of the two-stage-least-square regressions of CDS spreads. In the regressions, we include an interaction variable between fund holding share (FHS) and the maturity indicator variable, *Maturity indicator*. The maturity indicator variable takes the value of one if the firm has a maturing bond within the next month and zero otherwise. Control variables are identical to those in Table 2, whose coefficient estimates we do not report. *t*-statistics based on standard errors that are robust to heteroskedasticity and two-way clustered by firm and time are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: 5-year CDS spread (bps)	
	(1)	(2)
FHS (%)	1.578***	0.973***
	(4.24)	(2.69)
FHS (%) × Maturity indicator	1.641**	1.483**
	(2.34)	(2.18)
Maturity indicator	-56.780**	-55.631**
	(-2.42)	(-2.35)
Controls	YES	YES
Time FE	NO	YES
No. of obs.	45,462	45,459

Table 6. Fund Holdings and Credit Risk: Do Market Conditions Matter?

In this table, we present the estimation results of the two-stage-least-square regressions of CDS spreads for subsamples based on the default spread in columns (1) through (3) and the VIX in columns (4) through (6). We form subsamples based on the sample medians. In Panel A, we estimate the baseline regressions as in Table 2, whereas in Panel B, we include interaction variables with the maturity indicator as in Table 5. In columns (3) and (6), we report the difference in coefficient estimates between the two subsamples by running a pooled regression with each regressor interacted with the high credit spread or high VIX dummy, respectively, and report the corresponding *t*-statistics. The control variables are the same as in the baseline regression in Table 2. *t*-statistics based on standard errors that are robust to heteroskedasticity and two-way clustered by firm and time are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Baseline regressions using the subsamples

	Dependent variable: 5-year CDS spread (bps)					
	(1)	(2)	(3)	(4)	(5)	(6)
	High default spread	Low default spread	High – Low (*t*-stat)	High VIX	Low VIX	High – Low (*t*-stat)
FHS (%)	1.085**	0.846**	0.238	1.065**	0.894**	0.171
	(2.38)	(2.32)	(0.56)	(2.31)	(2.45)	(0.38)
Controls	YES	YES		YES	YES	
Time FE	YES	YES		YES	YES	
No. of obs.	25,368	20,091		25,174	20,285	

Panel B. Including interactions with the maturity indicator variable

	Dependent variable: 5-year CDS spread (bps)					
	(1)	(2)	(3)	(4)	(5)	(6)
	High default spread	Low default spread	High – Low (*t*-stat)	High VIX	Low VIX	High – Low (*t*-stat)
FHS (%)	1.036**	0.831**	0.205	1.027**	0.866**	0.161
	(2.27)	(2.24)	(0.48)	(2.23)	(2.34)	(0.36)
FHS (%)	2.367**	0.559	1.808*	1.997*	1.015*	0.982
× Maturity dummy	(2.19)	(1.01)	(1.79)	(1.75)	(1.90)	(0.89)
Maturity dummy	-90.048**	-19.509	-70.538**	-78.184*	-32.303**	-45.881
	(-2.33)	(-1.21)	(-2.04)	(-1.93)	(-2.04)	(-1.22)
Controls	YES	YES		YES	YES	
Time FE	YES	YES		YES	YES	
No. of obs.	25,368	20,091		25,174	20,285	

Table 7. Fund Characteristics, Fund Holdings, and Credit Risk

In this table, we report the estimation results of the two-stage least squares regressions of CDS spreads, using fund holding share (FHS) constructed separately for high- and low-group funds based on past 12-month fund returns (column 1), past 12-month fund flow volatility (column 2), management firm size (column 3), and the percentage of share classes with a load fee (column 4). We sort funds at each month end into above-median (high) and below-median (low) groups within each Lipper objective code. We also report F-statistics testing the hypothesis that the coefficients of high- and low-group FHS are equal. *t*-statistics based on standard errors that are robust to heteroskedasticity and two-way clustered by firm and time are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: 5-year CDS spread (bps)			
	(1)	(2)	(3)	(4)
Fund characteristic of interest	1-year fund return	1-year fund flow volatility	Management firm size	% of load fee classes
High-group FHS (%)$^{(H)}$	0.769*	2.238***	0.555	0.488
	(1.71)	(4.48)	(1.36)	(1.11)
Low-group FHS (%)$^{(L)}$	1.257***	0.522	2.233***	2.498***
	(3.00)	(1.15)	(3.63)	(4.78)
F-statistic: (H) = (L)	0.81	6.16**	5.59**	8.92***
Controls	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
No. of obs.	45,459	45,459	45,459	45,459

Table 8. Difference-in-Difference Test: Departure of Bill Gross

In this table we estimate the effect of Bill Gross' departure from PIMCO in September 2014 on credit risk of firms held by PIMCO, using difference-in-difference regressions. In Panel A, the treated firms are all firms held by PIMCO at the end of August 2014. We employ two sets of control firms: all sample firms or those held by Prudential or Vanguard. The indicator variable for the treated firms, *PIMCO*, takes the value of one for the treated firms. We employ an event window of [-6, 6] months around the departure of Bill Gross. The indicator variable, *Post-Bill Gross departure*, takes the value of one for the window of [0, 6] months after the Bill Gross departure. In Panel B, the treated firms are all firms held by PIMCO at the end of August 2014 with PIMCO holding share greater than 5% and the control firms are either all sample firms or those held by Prudential or Vanguard with the holding share exceeding 5%. In columns (3) and (4) we include interactions with indicator variables for firms rated A or above versus BBB or below. We report F-statistic testing the hypothesis that the two coefficients are equal. The control variables are the same as those in Table 2. *t*-statistics based on standard errors that are robust to heteroskedasticity and clustered by time are reported in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Treated firms: All firms held by PIMCO

	Dependent variable: 5-year CDS spread (bps)			
	All sample firms	PIMCO vs. Prudential or Vanguard	All sample firms	PIMCO vs. Prudential or Vanguard
	(1)	(2)	(3)	(4)
PIMCO × Post-Bill Gross departure	4.214*** (3.16)	7.344*** (4.02)		
PIMCO × *I*(A or above) × Post-Bill Gross departure(A)			-2.749 (-1.62)	1.769 (0.93)
PIMCO × *I*(BBB or below) × Post-Bill Gross departure(BBB)			6.885*** (3.66)	9.499*** (4.14)
F-statistic: (A) = (BBB)			11.79***	8.30**
Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Adjusted R-squared	0.958	0.926	0.958	0.926
No. of obs.	5,561	3,542	5,561	3,542

Panel B. Treated firms: Those with PIMCO holding share greater than 5%

	Dependent variable: 5-year CDS spread (bps)			
	All sample firms	PIMCO vs. Prudential or Vanguard	All sample firms	PIMCO vs. Prudential or Vanguard
	(1)	(2)	(3)	(4)
PIMCO × Post-Bill Gross departure	11.137*** (3.28)	13.663*** (3.35)		
PIMCO × *I*(A or above) × Post-Bill Gross departure(A)			2.938 (0.90)	10.362* (2.07)
PIMCO × *I*(BBB or below) × Post-Bill Gross departure(B)			12.508*** (3.33)	14.214*** (3.26)
F-statistic: (A) = (BBB)			5.38**	0.57
Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Adjusted R-squared	0.958	0.919	0.958	0.919
No. of obs.	5,561	3,399	5,561	3,399

Table 9. Fund Holdings and Credit Risk: The Role of Concavity in the Flow-Performance Relationship

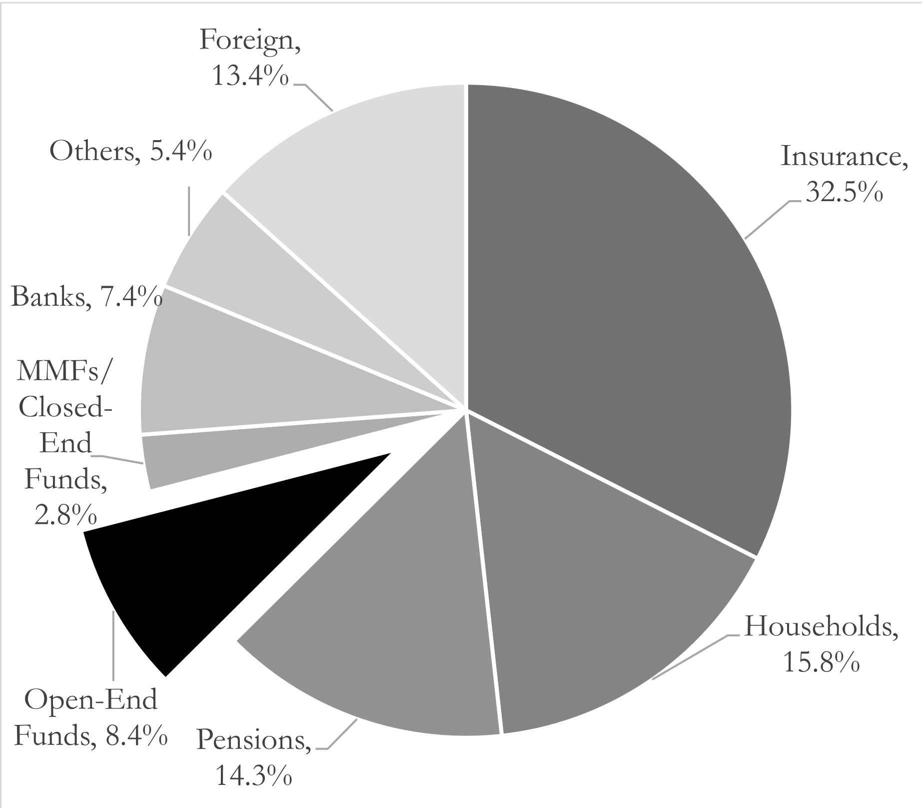
In this table, we estimate the two-stage least squares regressions of CDS spreads, using fund holding share (FHS) constructed separately for high-concavity and low-concavity funds. To sort funds into high- and low-concavity fund, we first estimate concavity in flow-performance sensitivity by running a three-year rolling regression of monthly flow on lagged return and the interaction of lagged return with a negative return indicator variable. The coefficient estimate on this interaction term is concavity in flow-performance sensitivity for the share class, which we aggregate to obtain fund-level concavity. We then sort funds into high- and low-concavity based on the sample median within each Lipper objective code. In column (1), we use FHS constructed separately from high and low concavity funds in the two-stage least square regressions. In column (2), we interact FHS with two mutually exclusive credit rating dummies (A or above vs. BBB or below). Control variables are identical to those in Table 2. *t*-statistics based on standard errors that are robust to heteroskedasticity and two-way clustered by firm and time are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: 5-year CDS spread (bps)	
	(1)	(2)
High concavity FHS (%)$^{(H)}$	0.427*** (2.96)	
Low concavity FHS (%)$^{(L)}$	0.296* (1.81)	
High concavity FHS × I(A or above)$^{(HA)}$		-0.275 (-1.62)
High concavity FHS × I(BBB or below)$^{(HB)}$		0.541*** (3.78)
Low concavity FHS × I(A or above)$^{(LA)}$		-0.166 (-0.77)
Low concavity FHS × I(BBB or below)$^{(LB)}$		0.346** (2.00)
F-statistic: (H) = (L)	0.71	
F-statistic: (HA) = (HB)		22.15***
F-statistic: (LA) = (LB)		5.16**
Time FE	YES	YES
No. of obs.	45,459	45,459

Figure 1. Who Holds Corporate Bonds? 1998 vs. 2017

Figures are from the Federal Reserve's Flow of Funds (L.213).

Panel A. 1998 Year-End



Panel B. 2017 Year-End

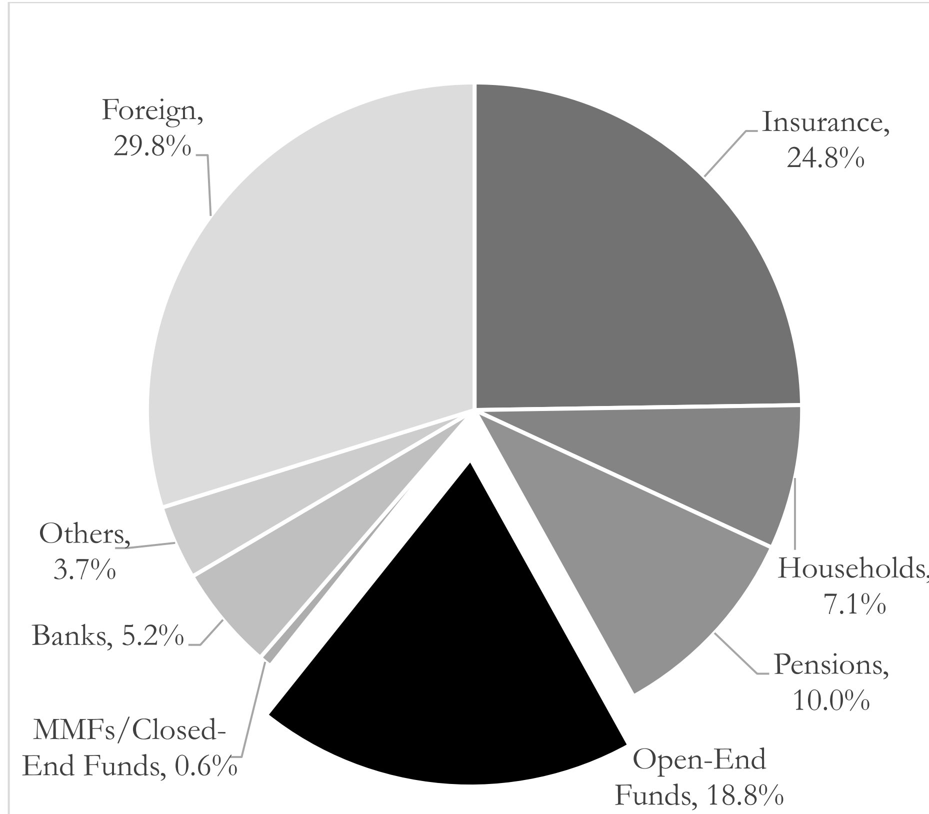


Figure 2. Bondholders With vs. Without Flow Concerns and Strategic Default

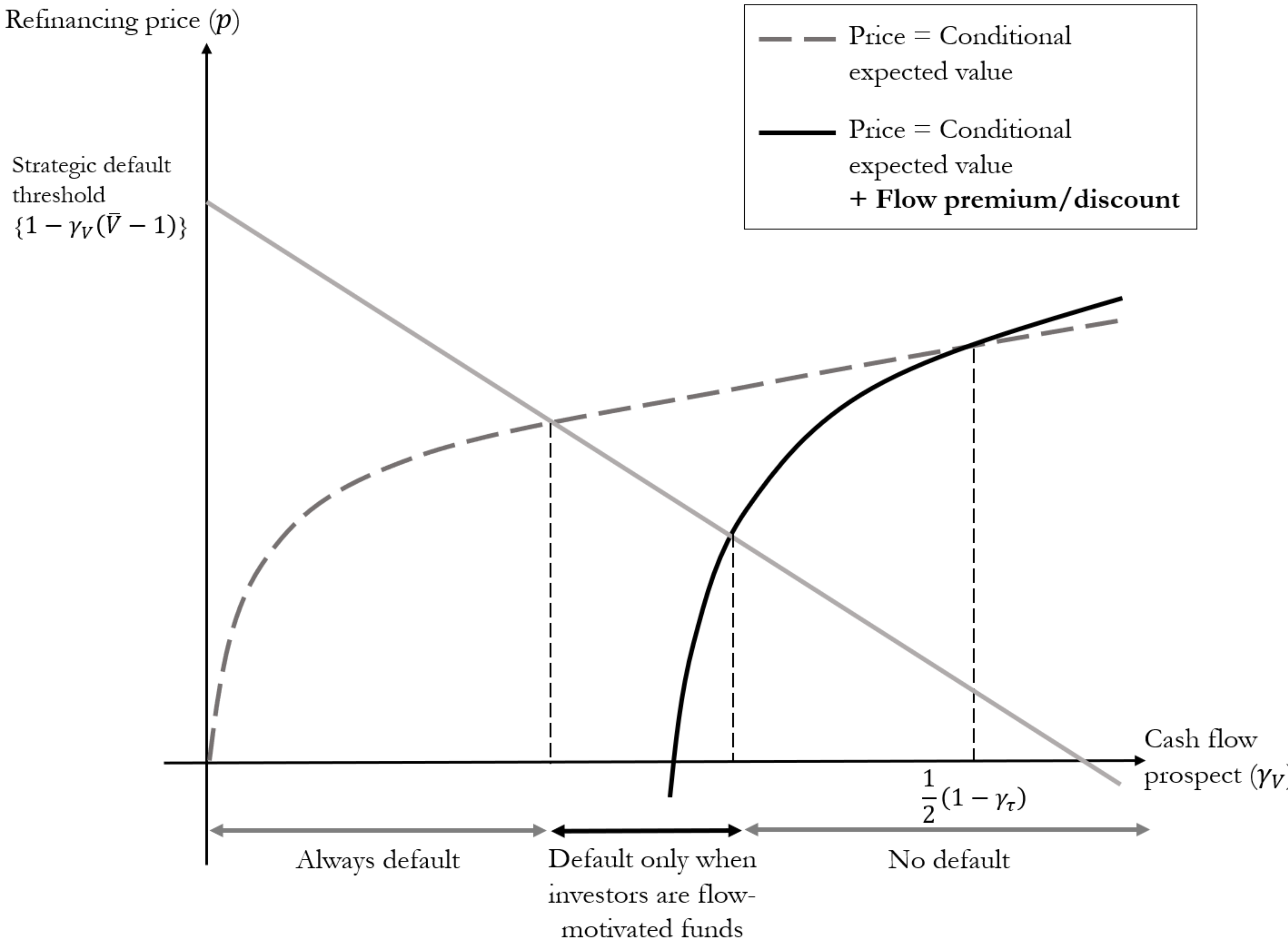
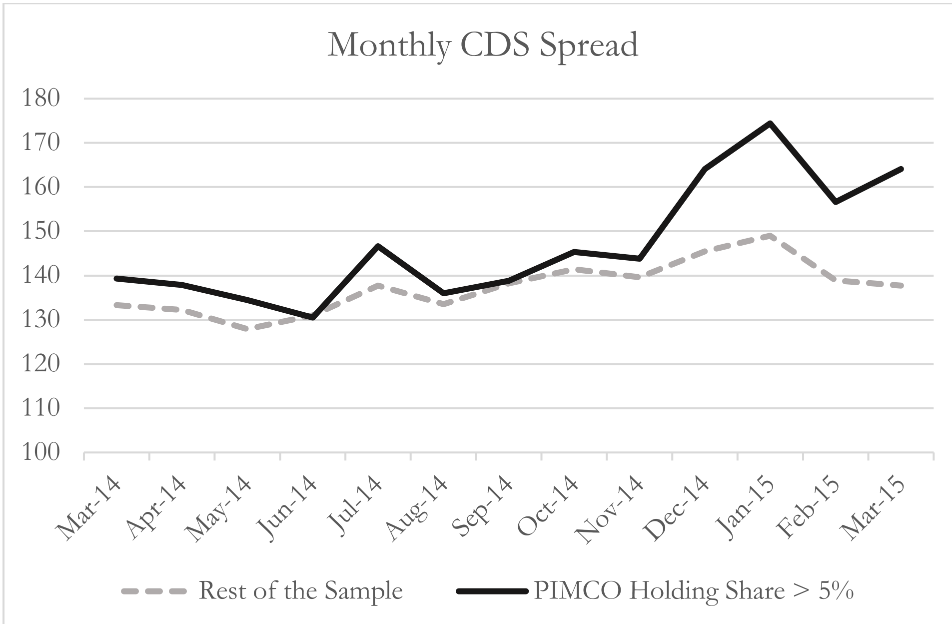


Figure 3. CDS Spreads of PIMCO and Control Firms around the Departure of Bill Gross

For all firms with PIMCO holding share greater than 5% in August 2014, we plot their monthly CDS spread over our [-6, 6] months of difference-in-difference test window. In Panel A, we compare their spreads with all other firms, while in Panel B we compare with firms with Prudential or Vanguard holding share greater than 5%.

Panel A. Control group: All sample firms



Panel B. Control group: Firms with Prudential or Vanguard holding share greater than 5% as controls

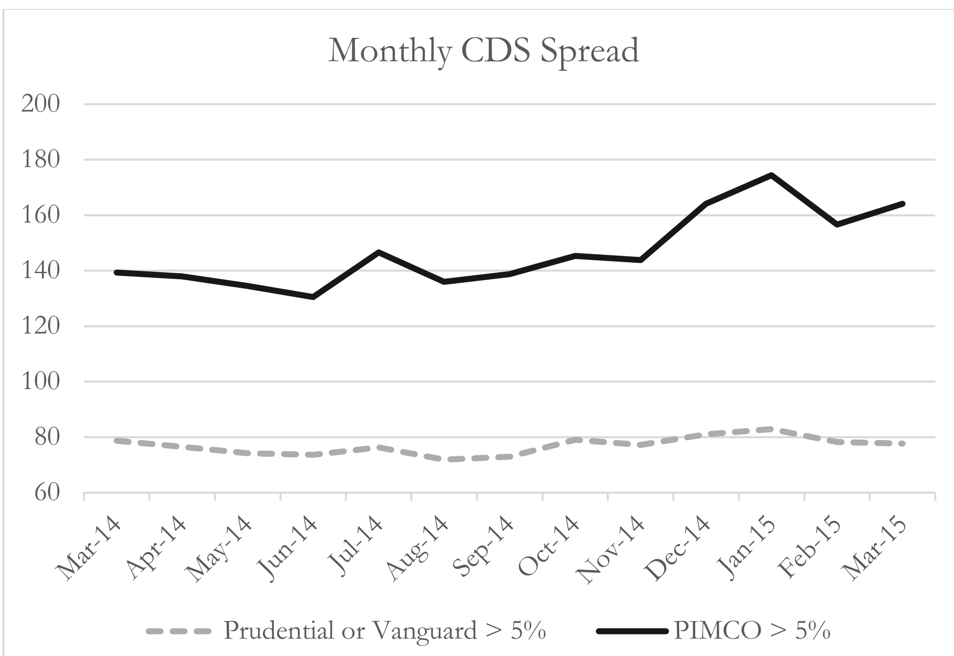
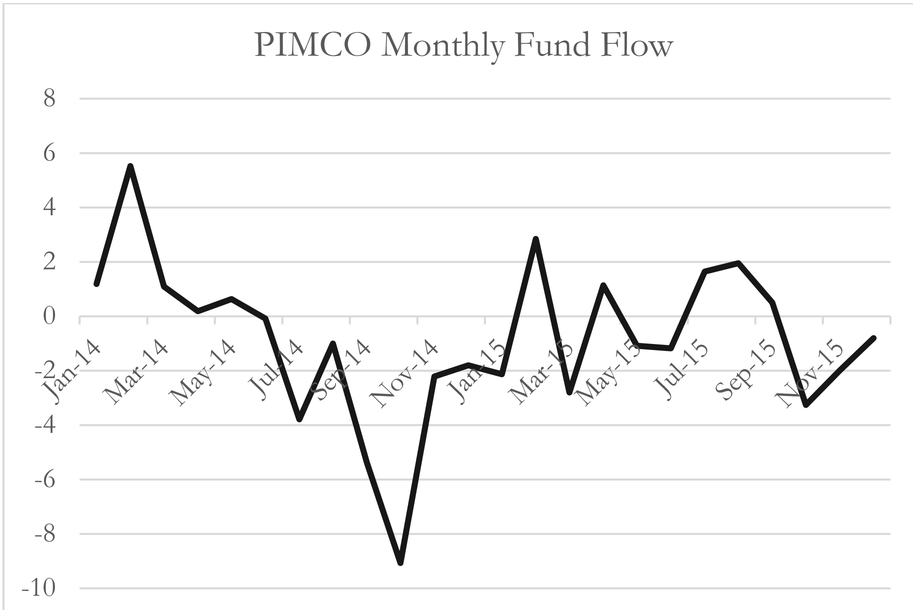


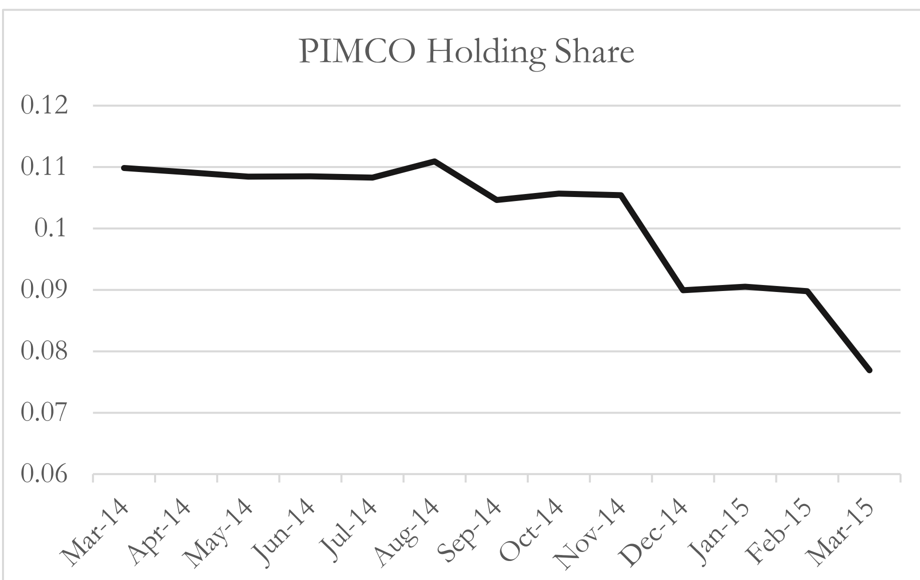
Figure 4. PIMCO Fund Flows and Holding Share Around the Departure of Bill Gross

In Panel A, we plot the monthly fund flows of PIMCO around the departure of Bill Gross in September 2014. In Panel B, for all firms held by PIMCO in their August 2014 holding, we plot these firms' PIMCO holding share over our [-6, 6] months of difference-in-difference test window. In Panel C, we plot the overall fund holding share of all firms held by PIMCO vs. Prudential or Vanguard over the same test window in Panel C.

Panel A. PIMCO monthly fund flows



Panel B. PIMCO's holding share of firms that PIMCO held in August 2014



Panel C. FHS of firms held by PIMCO vs. firms held by Prudential or Vanguard

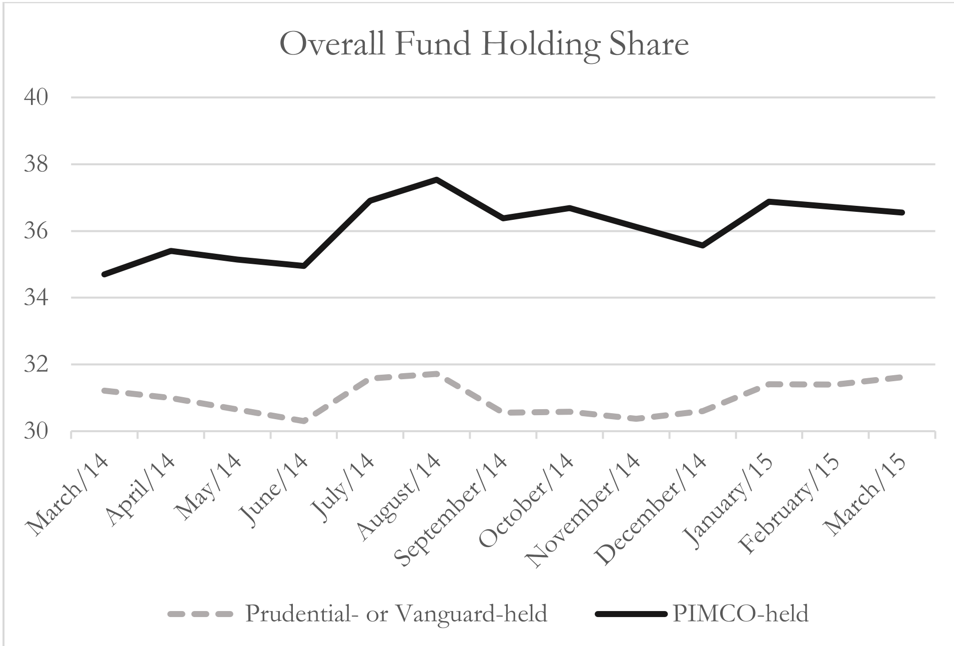
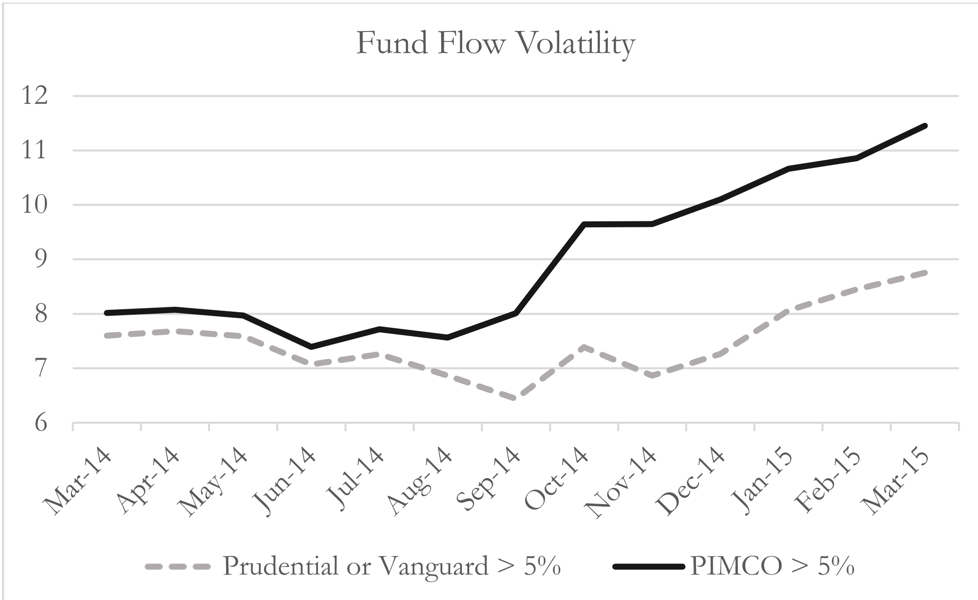


Figure 5. Fund Flow Volatility of PIMCO-Held Firms

For all firms with PIMCO holding share greater than 5% in August 2014, we plot their past 12-month fund flow volatility (in black). The firm-level flow volatility is calculated as the average of flow volatility of funds holding the firms, weighted by the funds' bond holdings. We also plot fund flow volatility for the control group of firms with Prudential or Vanguard holding share greater than 5% in August 2014 (in dashed gray).



Internet Appendix to "Bond Funds and Credit Risk"

This Version: March 28, 2022

Appendix A. Proofs

Proof of Proposition 2. Suppose that the firm sets the price of the bond as in (4). We then verify in steps that an equilibrium exists as outlined in the proposition.

Without loss of generality, consider a fund with $s = \bar{V}$. If the fund chooses to buy the bond, i.e., $a = 1$, its expected payoff is

$$\underbrace{\Pr(V = \bar{V}|s = \bar{V}) \cdot 1}_{\text{No default at } t=2} + \underbrace{\Pr(V = 0|s = \bar{V}) \cdot 0}_{\text{Default at } t=2} - p + \kappa E(\Pr(\tau = G|a = 1, V)|s = \bar{V}). \tag{A.1}$$

Substituting the price as stated in (4) yields this quantity to be $\kappa E(\Pr(\tau = G|a = 0, V)|s = \bar{V})$. Thus, upon receiving a high signal, the fund is indifferent between buying and not buying the bond; this represents the high signal funds' full willingness to pay for the bond. Thus, an equilibrium with $a = 1$ can be sustained.

Now consider a fund with $s = 0$. If the fund chooses $a = 1$, its expected payoff is

$$\underbrace{\Pr(V = \bar{V}|s = 0) \cdot 1}_{\text{No default at } t=2} + \underbrace{\Pr(V = 0|s = 0) \cdot 0}_{\text{Default at } t=2} - p + \kappa E(\Pr(\tau = G|a = 1, V)|s = 0), \tag{A.2}$$

which, upon substituting in the price, becomes

$$\begin{aligned} &\Pr(V = \bar{V}|s = 0) - \Pr(V = \bar{V}|s = \bar{V}) + \kappa\{E(\Pr(\tau = G|a = 0, V)|s = \bar{V}) + \\ &E(\Pr(\tau = G|a = 1, V)|s = 0) - E(\Pr(\tau = G|a = 1, V)|s = \bar{V})\}. \end{aligned} \tag{A.3}$$

Now, let $\sigma \equiv \gamma_\tau \sigma_G + (1 - \gamma_\tau)\sigma_B$ be the average precision of the fund. Knowing that $\sigma_G = 1$ and $\sigma_B = 1/2$, this quantity becomes $\sigma = \gamma_\tau + \frac{1}{2}(1 - \gamma_\tau) = \frac{1}{2}(1 + \gamma_\tau)$.

In this instance, we have the following:

$$\Pr(V = \bar{V}|s = \bar{V}) = \frac{\gamma_V \sigma}{\gamma_V \sigma + (1-\gamma_V)(1-\sigma)} = \frac{\gamma_V(1+\gamma_\tau)}{1-\gamma_\tau+2\gamma_V\gamma_\tau}, \tag{A.4}$$

$$\Pr(V=\bar{V}|s=0)=\frac{\gamma_V(1-\sigma)}{\gamma_V(1-\sigma)+(1-\gamma_V)\sigma}=\frac{\gamma_V(1-\gamma_\tau)}{1+\gamma_\tau-2\gamma_V\gamma_\tau}. \tag{A.5}$$

As long as the signal is informative, i.e.,. $\gamma_\tau>0$, we have $\Pr(V=\bar{V}|s=\bar{V})>\Pr(V=\bar{V}|s=0)$. Under the equilibrium strategies, a fund chooses $a=1$ if and only if $s=\bar{V}$. Then, due to the symmetric nature of the set-up, we have:

$$\Pr(\tau=G|a=1,V=\bar{V})=\Pr(\tau=G|a=0,V=0)=\frac{2\gamma_\tau}{1+\gamma_\tau}, \tag{A.6}$$

$$\Pr(\tau=G|a=0,V=\bar{V})=\Pr(\tau=G|a=1,V=0)=0. \tag{A.7}$$

If so, we have the following set of quantities:

$$E(\Pr(\tau=G|a=1,V)|s=\bar{V})=\frac{\gamma_V(1+\gamma_\tau)}{1-\gamma_\tau+2\gamma_V\gamma_\tau}\frac{2\gamma_\tau}{1+\gamma_\tau}, \tag{A.8}$$

$$E(\Pr(\tau=G|a=0,V)|s=\bar{V})=\left(1-\frac{\gamma_V(1+\gamma_\tau)}{1-\gamma_\tau+2\gamma_V\gamma_\tau}\right)\frac{2\gamma_\tau}{1+\gamma_\tau}, \tag{A.9}$$

$$E(\Pr(\tau=G|a=1,V)|s=0)=\frac{\gamma_V(1-\gamma_\tau)}{1+\gamma_\tau-2\gamma_V\gamma_\tau}\frac{2\gamma_\tau}{1+\gamma_\tau}, \tag{A.10}$$

$$E(\Pr(\tau=G|a=0,V)|s=0)=\left(1-\frac{\gamma_V(1-\gamma_\tau)}{1+\gamma_\tau-2\gamma_V\gamma_\tau}\right)\frac{2\gamma_\tau}{1+\gamma_\tau}. \tag{A.11}$$

A simple inspection reveals $E(\Pr(\tau=G|a=1,V)|s=0)-E(\Pr(\tau=G|a=1,V)|s=\bar{V})<0$, because $\Pr(V=\bar{V}|s=0)<\Pr(V=\bar{V}|s=\bar{V})$. This, along with the fact that $\Pr(V=\bar{V}|s=0)<\Pr(V=\bar{V}|s=\bar{V})$, ensures (A.3) is strictly less than $\kappa E(\Pr(\tau=G|a=0,V)|s=\bar{V})$.

We still need to compute the fund's payoff from choosing $a=0$ when $s=0$. This quantity is simply given by $\kappa E(\Pr(\tau=G|a=0,V)|s=0)$. However, from (A.9) and (A.11), it immediately follows that

$$E(\Pr(\tau=G|a=0,V)|s=0)>E(\Pr(\tau=G|a=0,V)|s=\bar{V}),$$

because $\Pr(V=0|s=0)>\Pr(V=0|s=\bar{V})$. This, along with our earlier result regarding the low signal fund's payoff, ensures that any fund with $s=0$ will be strictly better off choosing $a=0$.

The results so far indicate that, if the price is set as in (4), neither the high nor the low signal funds will have any incentive to deviate from the strategy outlined in the proposition. However, we still need to check the optimal strategy of the equityholders. Given that there is excess supply of potential bondholders, the firm does not need to lower the bond's issuance price to attract the funds with low signal, i.e., $s = 0$. Then, knowing that the bond will be held only by those with $s = \bar{V}$, the firm will charge up to their full willingness to pay, which, from our earlier part of the proof, is given by (4). Implicit in our proof is the argument that, if the firm were to charge a higher off-equilibrium price, the principals of the funds will not change their inferences conditional on the funds' actions. If so, $s = \bar{V}$ funds would not pay a price higher than their full willingness to pay, i.e., (4), and rollover would fail. □

Proof of Proposition 4. First, note that:

$$p_f^* - p^* = \kappa\{E(\Pr(\tau = G|a = 1, V)|s = \bar{V}) - E(\Pr(\tau = G|a = 0, V)|s = \bar{V})\}. \quad \text{(A.12)}$$

Using (A.8) and (A.9), this quantity will be negative if and only if

$$\frac{\gamma_V(1+\gamma_\tau)}{1-\gamma_\tau+2\gamma_V\gamma_\tau} < 1 - \frac{\gamma_V(1+\gamma_\tau)}{1-\gamma_\tau+2\gamma_V\gamma_\tau},$$

which, upon rearranging, reduces to $\gamma_V < \frac{1}{2}(1-\gamma_\tau)$. □

Proof of Proposition 5.

Part i: From Proposition 1, strategic default occurs whenever

$$p^* \equiv \frac{\gamma_V(1+\gamma_\tau)}{1-\gamma_\tau+2\gamma_V\gamma_\tau} \leq 1 - \gamma_V(\bar{V}-1). \quad \text{(A.13)}$$

The left hand side of (A.13) is increasing in γ_V for all $\gamma_\tau \in (0,1)$, with the derivative of $\frac{1-\gamma_\tau^2}{(1-\gamma_\tau+2\gamma_V\gamma_\tau)^2}$, while the right hand side, for all $\bar{V} > 1$, is decreasing in γ_V. Thus, it is easy to see that (A.13) will be satisfied as long as γ_V is less than or equal to some threshold $\bar{\gamma}_V(\bar{V})$ that is decreasing in $\bar{V}$. If so, for sufficiently large $\bar{V}$, it can always be guaranteed that $\bar{\gamma}_V(\bar{V}) < \frac{1}{2}(1-\gamma_\tau)$. At $\bar{\gamma}_V(\bar{V})$, equity holders would be exactly indifferent between strategically defaulting or not with profit-motivated bondholders, whereas with flow-motivated bondholders, they would strictly prefer to default. By continuity, for a positive-measure region to the immediate right of $\bar{\gamma}_V(\bar{V})$, there would be no strategic default if and only if bondholders are flow-motivated.

Part ii: For $\gamma_V > \frac{1}{2}(1-\gamma_\tau)$, strategic default never arises with profit-motivated bondholders because $\frac{1}{2}(1-\gamma_\tau) > \bar{\gamma}_V(\bar{V})$, and thus $\gamma_V > \bar{\gamma}_V(\bar{V})$. Strategic default also never arises with flow motivated bondholders because $p_f^* - p^* > 0$ for $\gamma_V > \frac{1}{2}(1-\gamma_\tau)$. □

Appendix B. Rollover under Pooling Equilibria

As discussed above, pooling equilibria are less natural in our context given that they do not generate a positive flow-performance relationship on the equilibrium path. That said, flow-motivated funds' reluctance to pay at rollover for firms with weak prospects survives qualitatively unchanged in pooling equilibria with reasonable off-equilibrium beliefs. To see this, consider the only possible pooling equilibrium with rollover, in which flow-motivated bondholders with signals $s = 0$ and $s = \bar{V}$ *both* buy (i.e., $a = 1$). Suppose the off-equilibrium choice of $a = 0$ is associated with the receipt of signal $s = 0$. This would indeed be the on-equilibrium inference if there was an infinitesimal measure of funds that refinanced "naively," i.e., bought if and only if they received the high signal. If so, these off-equilibrium beliefs are natural and robust.

It is easy to see, by analogy to Proposition 2, that the optimal pricing set by firms at rollover in such an equilibrium would be as follows:

$$p = \Pr(V = \bar{V}|s = 0) + \kappa\{\gamma_\tau - E(\Pr(\tau = G|s = 0, V)|s = 0)\}. \tag{B.1}$$

The second term of (B.1) represents the difference between the posterior reputation obtained by buying, which corresponds to the prior as no learning occurs in a pooling equilibrium, and the off-equilibrium reputation associated with not buying (under the off-equilibrium beliefs specified earlier). At such prices the fund manager with signal $s = 0$ would be indifferent between buying and not, while the fund manager with signal $s = \bar{V}$ would strictly prefer to buy.

It is clear that, for sufficiently low values of γ_V, we have:

$$p = \Pr(V = \bar{V}|s = 0) + \kappa\{\gamma_\tau - E(\Pr(\tau = G|s = 0, V)|s = 0)\} < \Pr(V = \bar{V}|s = 0), \tag{B.2}$$

because when the firm's prospects are sufficiently poor, the likely way to enhance reputation for a fund is to indicate via their action that they received $s = 0$. Thus, once again, poor corporate prospects will lead to lowered willingness to pay and result in a lower rollover price. This is further reinforced in a pooling equilibrium by the fact that $\Pr(V = \bar{V} | s = 0) < \Pr(V = \bar{V} | s = \bar{V})$, further lowering the rollover price relative to that in Proposition 3.

Appendix C. Variable Descriptions

In this appendix, we describe in detail how each variable used in our empirical analysis is constructed. Data source is denoted in parentheses.

C.1. Fund-level data

Fund holding share (Morningstar, CRSP Mutual Funds, TRACE, and Mergent FISD): For each bond at every month-end, we calculate the amount of bonds held by funds with the first two digits of CRSP objective codes "IC" or CRSP objective code "I," using each fund's latest available monthly or quarterly holdings data. We also compute the amount of bonds held by funds satisfying various characteristics, such as whether the previous 12-month return, rolling 12-month return volatility, or rolling 12-month flow volatility is above or below the sample median at the same point in time. For each fund, we further calculate the percentage of total assets held in institutional classes or classes with a load fee, with the latter defined as rear load fee applicable at the holding period of one month or minimum front load fee. We determine whether a fund is an index fund using the index fund flag in the CRSP Mutual Funds database, complemented with the name-based index fund identification of Berk and van Binsbergen (2015), and separately compute the amount of bonds held by active funds. We do so for every bond with Morningstar *sectype* code B, BF, or BI. We further obtain the latest amount outstanding of each bond from Mergent FISD. We then sum fund holdings and amount outstanding of all bonds issued by a firm satisfying the criteria above and divide the former with the latter to arrive at a fund-month level fund holding share of corporate bonds.

Fund flow (CRSP Mutual Funds): Using fund returns and total net assets from the CRSP Mutual Funds databases, we calculate the flow of fund i at month t:

$$Flow_{i,t} = \frac{TNA_{i,t} - (1 + r_{i,t})TNA_{i,t-1}}{TNA_{i,t-1}}, \tag{C.1}$$

where $TNA_{i,t}$ and $r_{i,t}$ are fund i's total net assets (TNAs) and monthly return at t, respectively. Share class level data are aggregated at the fund level using the CRSP identifier *crsp_cl_ grp* with TNAs at the previous month-end as the weight.

C.2. CDS Premium Data

Five-year CDS spread (Markit): Month-end CDS spread on five-year senior unsecured obligation contracts issued in U.S. dollars with modified restructuring clause until April 2009 and no restructuring clause thereafter.

C.3. Controls

Average credit rating and recovery rate (Markit): These are as reported in the Markit database.

Historical stock return (CRSP): 12-month stock returns computed using the CRSP database.

Historical return volatility, skewness, and kurtosis (CRSP): Rolling 12-month standard deviation, skewness, and kurtosis of daily stock returns using the CRSP database.

S&P 500 return (Compustat): Latest monthly return of the S&P 500 index.

VIX (Chicago Board of Exchange): Month-end VIX as reported by the Chicago Board of Exchange.

3-month T-Bill and term spread (FRED): 3-month T-Bill rate and the difference between the 10-year Treasury bond and 3-month T-Bill, respectively.

Log assets (Compustat): Log of total assets (*ATQ*) as reported in Compustat.

Leverage ratio (Compustat): The sum of current and long-term debt (*DLCQ* + *DLTTQ*), divided by the sum of current and long-term debt plus total stockholder equity (*DLCQ* + *DLTTQ* + *SEQQ*)

Return on equity (Compustat): Total income before extraordinary items (*IBQ*) divided by total stockholder equity (*SEQQ*)

Dividend payout per share (Compustat): Dividend payout per share (*DVPSPQ*) as reported in Compustat.

Appendix D. Internet Appendix Tables

Table A.1. Fund-underwriter-issuer relationship

For the sample of corporate bond issuances between 2000 and 2015, with corporate bonds in the Mergent FISD database defined as in Choi, Hoseinzade, Shin, and Tehranian (2020), we check the relationship between funds, underwriters, and issuers. First, we check the issuer-underwriter relationship by examining whether the issuer has used one or more of the lead underwriters in at least one of its previous issues within the past one or three years. Second, we check the fund-underwriter relationship by examining whether funds that purchase a new bond in the primary market (defined as an entry in the Morningstar holdings within the first 90 days of the offering date) have bought another bond underwritten by one of the lead underwriters within the past one or three years.

	Previous relationship in the primary market	No previous relationship in the primary market
Issuer-underwriter within:		
Past one year	82.0%	18.0%
Past three years	86.7%	13.3%
Fund-underwriter within:		
Past one year	95.4%	4.6%
Past three years	96.3%	3.7%

Table A.2. Robustness Check: Alternative Return Horizons

In this table we estimate the two-stage least squares regressions of CDS spreads on the interaction between fund holding share (FHS) and stock returns as in Table 2 Panel B but using past 1- and 6-month stock returns instead. Controls are identical to those in Table 2 Panel B, whose coefficient estimates we do not report. *t*-statistics based on standard errors that are robust to heteroskedasticity and two-way clustered by firm and time are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: 5-year CDS spread (bps)			
	(1)	(2)	(3)	(4)
	1-month return		6-month return	
FHS (%)	1.133***	0.946**	1.492***	1.186***
	(2.99)	(2.56)	(3.93)	(3.16)
FHS × stock return measure (%)	-3.469*	-3.883**	-2.946***	-3.180***
	(-1.76)	(-2.14)	(-3.31)	(-3.66)
Stock return measure (%)	-1.005	-0.489	-0.860***	-0.514
	(-1.50)	(-0.80)	(-2.65)	(-1.63)
Controls	YES	YES	YES	YES
Time FE	NO	YES	NO	YES
No. of obs.	45,462	45,459	45,462	45,459

Table A.3. Insurance Company, Pension Fund, and Passive Fund Holding Share

In this table we estimate the two-stage least squares regressions of CDS spreads, but using the insurance company, pension fund, passive fund holding shares as the main variable of interest instead. We use the Morningstar holdings data to calculate the passive fund holding share, while we use Thomson Reuters eMaxx data to compute the insurance and pension holding shares in the identical manner to the fund holding share as outlined in Table 2. We further compute the hypothetical holding share measure of Koijen and Yogo (2019) in an analogous manner for each institutional investor group. Columns (1) through (3) present the results for the baseline regressions as in Table 2, while in columns (4) through (6), we interact each group's holding share with the credit rating indicators as in Table 3 Panel A. In all instances, we include time fixed effect. Controls are identical to those in Table 2, whose coefficient estimates are omitted for brevity. *t*-statistics based on standard errors that are robust to heteroskedasticity and two-way clustered by firm and time are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: 5-year CDS spread (bps)					
	(1)	(2)	(3)	(4)	(5)	(6)
Institution of interest:	Insurance	Pension	Passive fund	Insurance	Pension	Passive fund
Institutional holding share	-1.734*** (-6.30)	-6.870*** (-3.43)	-3.305*** (-3.88)			
Institutional holding share × I(A or above) (%)$^{(A)}$				-1.955*** (-7.15)	-8.607*** (-4.13)	-3.074*** (-3.12)
Institutional holding share × I(BBB or below) (%)$^{(BBB)}$				-1.535*** (-4.92)	-5.216* (-1.90)	-3.376*** (-3.95)
Kleibergen-Paap F-statistic	386.20	427.10	119.14	190.83	127.91	59.17
F-statistic: (A) = (BBB)				5.55**	1.59	0.23
Controls	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
No. of obs.	44,297	44,297	45,459	44,297	44,297	44,297

Table A.4. Fund Holdings and Offering Yield

In this table we present the results of two-stage least squares regressions of CDS spread on fund holding share (FHS) as well as its interaction with credit rating indicators, but with the offering yield of a firm's new bond issuance as the dependent variable. Offering yield is defined as the offering-amount-weighted-average offering yield of a firm's bonds issued during the month. We focus our attention on all firm-months with bond issuance in columns (1) and (3), while we focus on bond issuances occurring within six months of a bond's maturity in (2) and (4), which we refer to as "rollover issues." Columns (1) and (2) present the baseline regressions in Table 2, while columns (3) and (4) present the regression results with FHS interacted with credit rating indicators. In all instances, we include time fixed effect. Controls are identical to Table A.3, whose coefficient estimates are omitted for brevity. *t*-statistics based on standard errors that are robust to heteroskedasticity and two-way clustered by firm and time are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: Offering yield (bps)			
	(1)	(2)	(3)	(4)
Issuances	All	Rollover	All	Rollover
FHS (%)	1.485***	1.520**		
	(4.51)	(2.43)		
FHS ×			-2.207**	-2.156
I(A or above) (%) (A)			(-2.56)	(-1.58)
FHS ×			1.900***	2.090***
I(BBB or below) (%) (BBB)			(5.82)	(3.88)
F-statistic: (A) = (BBB)			23.23***	12.15***
Controls	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
No. of obs.	4,356	1,690	4,347	1,690

Table A.5. Difference-in-Difference Test: PIMCO's Flow-Performance Sensitivity

In this table we run monthly regression of fund share class flow on the triple interaction between fund share class return, PIMCO indicator, and post-Bill Gross departure indicator. We run a monthly flow regression in a similar set-up to Choi, Kronlund, and Oh (2021) for the window of [-6, 6] month around the departure of Bill Gross for the sample of all corporate and general bond funds. Regressions are run at the fund share class-month level. Controls include lagged fund share class flow, fund share class size, management firm size, fund age, passive fund dummy, institutional share class dummy, turnover ratio, expense ratio, and load fund class dummy, with the variable definition identical to Choi, Kronlund, and Oh (2021). Returns and all fund characteristics are lagged by one month. We include Lipper-objective-by-time fixed effect. *t*-statistics based on standard errors that are robust to heteroskedasticity and clustered by month are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: fund share class flow (%)
Fund share class return (%)	0.855 (1.63)
PIMCO	-1.962*** (-4.61)
Fund share class return (%) × PIMCO	0.601 (0.71)
Fund share class return (%) × Post Bill Gross departure	-0.302 (-0.54)
PIMCO × Post Bill Gross departure	-3.640 (-1.56)
Fund share class return (%) × PIMCO × Post Bill Gross departure	**6.680**** **(2.87)**
Lagged fund share class flow (%)	0.152*** (9.57)
Fund share class size	-0.158*** (-6.04)
Management firm size	0.063 (1.45)
Fund age	-0.125*** (-16.66)
Passive fund dummy	-0.671** (-2.51)
Turnover ratio	0.049 (0.69)
Expense ratio	-1.849*** (-8.66)
Institutional class dummy	0.120 (0.54)
Load class dummy	-0.358** (-2.44)
Lipper-objective-by-time FE	YES
Adjusted R-squared	0.068
No. of obs.	25,192

Table A.6. Difference-in-Difference Test: Longer Test Window

In this table we estimate the effect of Bill Gross' departure from PIMCO in September 2014 on credit risk of firms held by PIMCO, using difference-in-difference regressions as in Table 8, but for a longer test window of [-12, 12] months around his departure. *t*-statistics based on standard errors that are robust to heteroskedasticity and clustered by month are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. All firms held by PIMCO

	Dependent variable: 5-year CDS spread (bps)			
	All sample firms	PIMCO vs. Prudential or Vanguard	All sample firms	PIMCO vs. Prudential or Vanguard
	(1)	(2)	(3)	(4)
PIMCO × Post-Bill Gross departure	7.567*** (3.24)	11.637*** (3.62)		
PIMCO × *I*(A or above) × Post-Bill Gross departure[(A)]			-4.377*** (-2.94)	-0.080 (-0.04)
PIMCO × *I*(BBB or below) × Post-Bill Gross departure[(BBB)]			12.146*** (3.58)	16.136*** (3.87)
F-statistic: (A) = (BBB)			15.74***	16.59***
Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Adjusted R-squared	0.918	0.859	0.918	0.859
No. of obs.	10,652	6,727	10,652	6,727

Panel B. Firms with PIMCO holding share greater than 5%

	Dependent variable: 5-year CDS spread (bps)			
	All sample firms	PIMCO vs. Prudential or Vanguard	All sample firms	PIMCO vs. Prudential or Vanguard
	(1)	(2)	(3)	(4)
PIMCO × Post-Bill Gross departure	20.134*** (3.73)	22.477*** (3.68)		
PIMCO × *I*(A or above) × Post-Bill Gross departure[(A)]			-0.343 (-0.06)	3.781 (0.50)
PIMCO × *I*(BBB or below) × Post-Bill Gross departure[(BBB)]			23.517*** (4.16)	25.557*** (4.11)
F-statistic: (A) = (BBB)			19.30***	13.62***
Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Adjusted R-squared	0.918	0.850	0.918	0.851
No. of obs.	10,652	6,452	10,652	6,452

Table A.7. Fund Holding Share and Cash Flow Volatility

In this table we run OLS regressions of fund holding share (FHS) on proxies of first two moments of cash flows. First, in column (1), we use 1-year stock return and realized volatility, the latter of which is annualized volatility of daily stock returns during the previous month. In column (2), we consider ROE and the volatility of profitability (VOLP) measure of Pastor and Veronesi (2003). We further include log assets, leverage ratio, and dividend payout per share as controls. All controls are lagged by one month, and we omit their coefficient estimates for brevity. Regressions are conducted at firm-month level with firm and time fixed effects. *t*-statistics based on standard errors that are robust to heteroskedasticity and two-way clustered by firm and time are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: FHS (%)	
1-year stock return (%)	0.015*	
	(1.75)	
Realized volatility	2.640	
	(1.55)	
ROE (%)		-0.036**
		(-2.24)
VOLP		0.131
		(0.13)
Controls	YES	YES
Firm FE	YES	YES
Time FE	YES	YES
Adjusted R-squared	0.504	0.522
No. of obs.	45,956	40,356

Table A.8. Fund Holding and the Firm's Total Debt

In this table, we estimate the two-stage least squares regressions of CDS spreads, but with an alternative definition of the fund holding share (FHS). Specifically, we construct FHS by dividing the amount of active funds' bond holdings with a firm's total debt (*DLCQ* + *DLTTQ* in the latest Compustat quarterly data) instead. Panel A presents the baseline regressions as in Table 2, while we interact FHS with credit rating indicators as in Table 3 Panel A in Panel B. Panel C presents the regression results with FHS interacted with the maturity indicator, and Panel D presents the results with high- and low-group FHS computed on the basis of various fund characteristics as in Table 7. *t*-statistics based on standard errors that are robust to heteroskedasticity and two-way clustered by firm and time are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Baseline regressions

	Dependent variable: 5-year CDS spread (bps)	
	(1)	(2)
FHS (%)	1.046***	0.680*
	(2.66)	(1.74)
Controls	YES	YES
Time FE	NO	YES
Kleibergen-Paap F-statistic	195.84	191.00
No. of obs.	45,454	45,451

Panel B. Credit rating interactions

	Dependent variable: 5-year CDS spread (bps)	
	(1)	(2)
FHS (%) ×	-0.979*	-0.893
I(A or above)$^{(A)}$	(-1.67)	(-1.62)
FHS (%) ×	1.122***	0.730*
I(BBB or below)$^{(BBB)}$	(2.84)	(1.85)
F-statistic: (A) = (BBB)	19.46***	12.19***
Controls	YES	YES
Time FE	NO	YES
No. of obs.	45,454	45,451

Panel C. Maturity dummy interactions

	Dependent variable: 5-year CDS spread (bps)	
	(1)	(2)
FHS (%)	1.475***	0.652*
	(3.89)	(1.66)
FHS (%) ×	1.141**	1.327**
Maturity indicator	(2.03)	(2.28)
Maturity indicator	-28.415**	-33.184**
	(-2.24)	(-2.45)
Controls	YES	YES
Time FE	NO	YES
No. of obs.	45,454	45,451

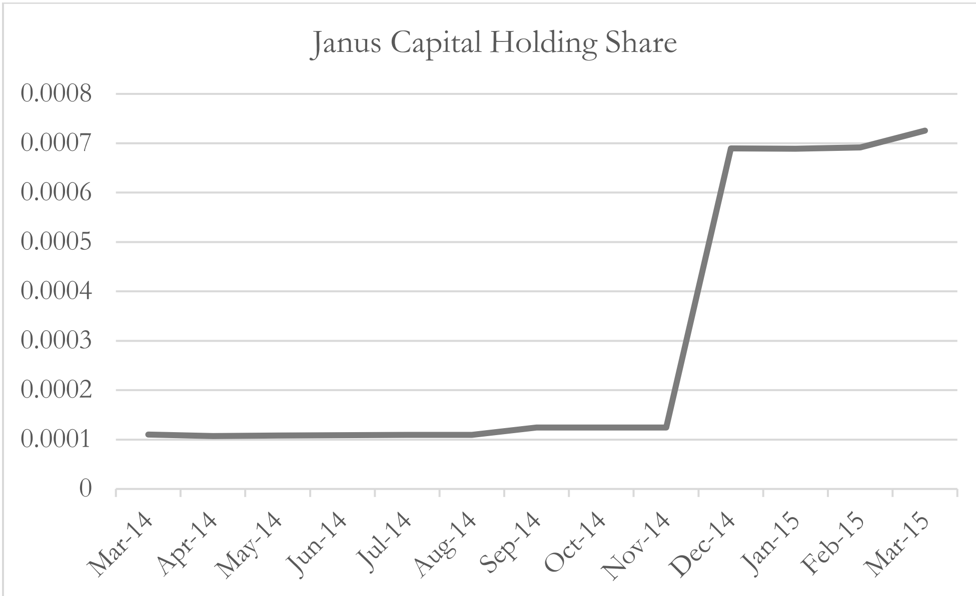
Panel D. Fund characteristics

	Dependent variable: 5-year CDS spread (bps)			
	(1)	(2)	(3)	(4)
Fund characteristic of interest	1-year fund return	1-year fund flow volatility	Management firm size	% of load fee classes
High-group FHS (%)[(H)]	0.874	2.411***	-0.051	-0.207
	(1.45)	(2.78)	(-0.09)	(-0.42)
Low-group FHS (%)[(L)]	0.418	-0.091	2.294**	3.479***
	(0.58)	(-0.13)	(2.35)	(4.07)
F-statistic: (1) = (2)	0.20	3.33*	3.05*	11.50***
Controls	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
No. of obs.	45,451	45,451	45,451	45,451

Figure A.1. More on Fund Holding Shares Around the Departure of Bill Gross

In Panel A, for all firms held by PIMCO in August 2014, we plot these firms' Janus Capital holding share around our difference-in-difference analysis test window. In Panel B, we track the sum of Prudential- and Vanguard-holding shares for (i) all firms and for (ii) all firms held by PIMCO in August 2014.

Panel A. Janus Capital holding share



Panel B. Prudential and Vanguard holding shares